ISSUES IN INVESTMENT RISK: A SUPPLY-SIDE AND DEMAND-SIDE ANALYSIS OF THE AUSTRALIAN MANAGED FUND INDUSTRY

A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

By

Terrence Anthony Hallahan
BEc(Monash) Grad Dip Corp Fin (SUT) MComm (Melb)

School of Economics, Finance and Marketing
RMIT University
Melbourne

December 2005

Declaration

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; and, any editorial work, paid or unpaid, carried out by a third party is acknowledged.

Terrence A Hallahan

Acknowledgements

My thanks go to my original senior supervisor, Professor Robert Faff, for his guidance, support and patience. Thank you for your inspiration and encouragement and the sharing and discussion of ideas. Thank you also to Professor Richard Heaney for his involvement in the supervision of the thesis.

Thank you to Geoff Davey of FinaMetrica Ltd. for making available the large database of risk tolerance profiles.

I would also like to thank RMIT University, and my friends and colleagues in the School of Economics, Finance and Marketing for their support and encouragement. In particular, I would like to thank Associate Professor Michael McKenzie for data assistance and research discussions in respect to Chapters 2, 3 and 4 of the thesis.

I acknowledge and appreciate the advice and assistance of Ms Janine Halliwell in finalisation of the formatting of the thesis.

Finally, I wish to express my gratitude to my family; for their continued support, and allowing me to keep things in perspective.

Table of Contents

List of Tables

List of Figures

Summary

The investment management industry has proven to be a fertile ground for theoretical and empirical research over the past forty years, particularly in relation to the nature and quantification of risk. However, the dominance of the U.S. industry has meant that much of the academic research has focused on the U.S. market. This thesis investigates aspects of investment risk using alternative data to that used in much of the prior published research.

This thesis contains an extensive analysis of aspects of risk related to both the demand side and the supply side of the managed funds market in Australia. Among the demand side characteristics, attitudes towards risk and their impact on asset allocation decisions will be an important determinant of investors' financial well-being, particularly in retirement. Accordingly, the first part of the thesis examines the financial risk tolerance of investors, exploring the relationship between subjective financial risk tolerance and a range of demographic characteristics that are widely used as a basis for heuristically derived estimates of investors' attitudes towards financial risk.

The second part of the thesis contains an analysis of the supply side of the industry, focusing on risk-shifting behavior by investment fund managers. Since the time when performance and risk-shifting behavior of fund managers was first put under the spotlight 40 years ago, it is possible to identify an evolving strand in the research where performance assessment is examined within the framework of the principal-agent literature. One focus that has emerged in this literature is the adaption of the tournament model to the analysis of investment manager behavior, wherein it is hypothesized that fund managers who were interim losers were likely to increase fund volatility in the latter part of the assessment period to a greater extent than interim winners.

Against this background, the second part of the thesis examines risk-shifting behavior by Australian fund managers. Both the ability of fund managers to time the market and the applicability of the tournament model of funds management to a segment of the Australian industry are examined.

Chapter 1: Introduction

1.1. General Motivation

The global managed fund industry has recorded substantial growth over the last 15 years. Total assets of open-end investments companies worldwide have increased from $US1.1 trillion in 1990 to $US 16.2 trillion in 2004, with U.S. funds accounting for 50-60 percent of those assets over the period.[1] During this time Australian managed funds have increased their share of the world total managed fund assets from 1.2 percent to 3.9 percent. While this seems a small share compared to the U.S. total, in 2004 it places Australia as the fourth largest market worldwide behind Luxembourg (8.6 percent) and France (8.5 percent), and ahead of Italy (3.2 percent), the United Kingdom (3.1 percent), Ireland (2.9 percent) and Japan (2.5 percent).

The growth in managed funds in Australia has to a large extent been driven by changes to the retirement income system in Australia. The Australian Government's retirement provision policies have the aim of shifting the burden of funding retirement incomes from the public sector to the private sector. To facilitate this, a system of mandatory superannuation contributions for employees was introduced through Federal Government legislation in July 1992, and employers are now required to contribute 9% of an employee's wage to a superannuation fund account. As a consequence, superannuation funds have become the principal retirement savings vehicle for Australians, and the dominant component of the managed funds industry in Australia, increasing from around 65 per cent of the $AUS 192 billion of total managed funds in 1989 to around 83 per cent of the $AUS 813 billion of total funds under management in 2004.[2]

---

[1] Source: Investment Company Institute Mutual Fund Factbook, 1996 and 2005.
[2] Source: Reserve Bank of Australia Bulletin Statistical Tables, Table B18 Managed Funds, June 2005.

The shift to private sector funding of retirement incomes and the concomitant growth of investment funds has had two effects, one effect manifesting on the investor, or demand side of the industry, and the other effect impacting on the asset management, or supply side.

Firstly, on the demand side, individuals have been forced to become more financially aware, if not financially literate, as they have had greater responsibility for their future financial welfare imposed on them. While their involvement in securing an adequate retirement income might fall short of direct responsibility for investment decision-making, there has nevertheless has been an increasing interest in investment markets and the relationship between investment risk and return. Inevitably, attitudes towards bearing investment risk and the consequences for future financial welfare of differences in attitudes to bearing this risk have received increased attention.

Secondly, on the supply side, the growth in the amount of investment funds has meant that the structure, conduct and performance of the investment management industry have come under much closer scrutiny. In particular, the competitive conduct of the fund management industry and the risk-adjusted performance of managed funds have been subject to extensive examination by academic researchers and regulatory bodies.

1.2. Risk and Return in the Investment Management Industry

The seminal work of Markowitz (1952, 1959) is widely considered to have revolutionized the investment management process and, consequently, the investment management industry. Markowitz's portfolio theory provides a means for investors and investment managers to quantify and link investment risk and returns, and to identify and construct portfolios that, through appropriate combinations of assets, offer an optimal trade-off of risk and return.

One of the fundamental assumptions underlying Markowitz's work is that investors are risk-averse, meaning that they require higher returns in compensation for bearing higher risk. Given the well documented positive relationship between investment risk and return, it is evident that a precondition for identifying the optimal risk-return trade-off for an investor is to establish the investor's degree of risk aversion. In the practitioner community, risk aversion usually takes the guise of its inverse, risk tolerance. Portfolio selection therefore involves constructing or selecting a portfolio that offers a risk-return combination that matches the risk tolerance of the investor.

The managed fund industry offers products that represent different risk-return trade-offs. Risk tolerance and return expectations for a managed fund are predefined, and typically expressed in the funds' stated objectives. An investor selects a fund based upon its advertised characteristics and objectives. Because of the predefinition of the risk-return trade-off offered by the fund, the crucial objective of fund management is maximization of return in conjunction with maintenance of the advertised risk profile.

The centrality of the risk-return relationship to investment management is therefore manifest in the process of identifying managed investment funds that correspond to the varying risk tolerances of investors. This core relationship also provides a unifying foundation upon which the economic concepts of the supply-side and the demand-side of markets can be used as a framework in this thesis to examine aspects of risk and investment.

1.3. Motivation for Investigating the Australian Managed Funds Industry

While the growth of the managed fund industry has been a worldwide phenomenon, the dominance of the U.S. industry has inevitably meant that much of the academic research has focused on the U.S. market. The geographic narrowness of academic studies of mutual funds was commented on recently by Khorana, Servaes and Tufano (2005), and concerns about data snooping in finance research because of the focus on U.S. data were raised some time ago, initially by Leamer (1980) and later by Lo and MacKinley (1990).

The contribution of this thesis is therefore to investigate aspects of investment risk using alternative data to that used in much of the prior published research. While, as noted above, the Australian managed funds industry is the fourth largest in the world, there has been little academic investigation of either investors' attitudes to risk or fund managers' manipulation of fund risk in the Australian market.

1.4. Investment Risk From The Demand Side

The flow of retirement savings in the financial system can be viewed as creating a demand for suitable investment products. One of the defining characteristics of this demand is the existence of differing attitudes towards risk on the part of investors.

Financial risk tolerance is a term widely used in the personal financial planning industry to refer to an investor's attitude towards risk. It can be defined as the amount of uncertainty or investment return volatility that an investor is willing to accept when making a financial decision (Grable, 2000; Grable and Lytton, 1999). This thesis uses a database consisting of psychometrically derived financial risk tolerance scores as well as respondents' demographic characteristics to examine the relationship between subjective financial risk tolerance and a range of demographic characteristics that are widely used as a basis for heuristically derived estimates of investors' attitudes towards financial risk.

1.5. Investment Risk From The Supply Side

As noted above, the managed fund industry offers a supply of products characterized by predefined risk-return trade-offs. While this attribute serves to differentiate products in the marketplace, it also acts as a constraint upon the extent of a fund manager's ability to alter the risk profile of a portfolio.

The well documented positive relationship between return and risk means that fund managers have an incentive to increase the risk profile of their portfolios in the search for higher returns. One way to achieve higher returns is through successful market timing, also known as macroforecasting. Timing ability is characterized as a decision by a manager to be in or out of the equity market, where being out of the (higher risk) equity market implies being in the (lower risk) fixed income market. As a result of fund managers effecting changes in the risk level of the portfolio, the relationship between portfolio returns and market returns will be non-linear. This thesis explores this non-linearity and identifies changes in the systematic risk of a sample of Australian equity funds through the use of a quadratic regression technique and the application of a 'dual beta' market model specification.

Another facet of risk-changing behavior by fund managers is explored through the tournament model of fund management. The literature on tournaments has its origins in the personnel economics area and initially focused on employment contracts. The extension of the tournament model to the funds management area began with Brown, Harlow and Starks (1996), who characterized the managed funds industry as a multi-period, multi-game tournament and focused on the possible strategic responses of funds identified at interim ranking stages as likely to be ultimate “winners” or “losers”. Brown et al. (1996) hypothesized that fund managers who were interim losers (below the median performance for the first part of the assessment period), were likely to increase fund volatility in the latter part of the assessment period to a greater extent than interim winners. This strategy of increasing volatility was based on the expectation that higher volatility gave the losing manager a better chance of a major performance reversal that would redeem their ranking and, hence, secure a major tournament prize at year end.

This thesis contributes to the fund management literature by exploring tournament behavior among managers of Australian multi-sector growth funds. Two analyses are undertaken, firstly using a non-parametric contingency table analysis and secondly using a regression-based approach.

1.6. Scope and Structure of The Thesis

This thesis explores aspects of investment risk in financial markets from both the demand side and the supply side. The thesis comprises six research essays presented in Chapters 2 to 7. On the demand side there are three essays dealing with investor risk tolerance and on the supply side three essays dealing with changes to portfolio risk initiated by fund managers. Since each chapter explores a separate research issue the relevant literature is reviewed within each chapter. Overall, the thesis forms a substantial analysis of aspects of investment risk. An overview of each chapter is presented below.

1.6.1. Demand Side Essays

The first essay, in Chapter 2, examines the relationship between subjective financial risk tolerance and a range of demographic characteristics that are widely used as a basis for heuristically derived estimates of investors' attitudes towards financial risk. There is a large body of extant research that has focused on the use of demographic characteristics to predict investor risk tolerance.[3] The sample used in this Chapter comprised 3124 respondents who completed a risk profile in January-February 2002. The contribution of this paper is to provide further evidence on the validity of these heuristics by examining the relationship between a psychometrically derived measure of subjective risk tolerance and responses to questions on eight demographic characteristics. Our results indicate that gender, age, income and net wealth are important determinants of an individual's attitude towards risk. However, education, marital status and the number of dependents were all found to be insignificant in determining risk tolerance in the sample group.

Chapter 3 continues the demand side focus and provides further evidence as to the behavior and 'determinants' of investor risk tolerance. In addition to an analysis of the relationship between risk tolerance and general demographics, special attention is given to issues surrounding age and marital status. While most studies in this area use small samples, the database used in this study consists of a psychometrically derived financial risk tolerance score (RTS) for over 20,000 surveyed individuals as well as each respondent's demographic characteristics. Analysis of the data reveals that while peoples self-assessed risk tolerance and the psychometrically-derived RTS generally accord, there is considerable variation with a tendency for respondents to under-estimate their risk tolerance. The practical implication of this analysis is that financial planners and investment advisors who rely largely on subjective

[3] For a survey see Grable and Lytton (1998) and Grable and Joo (1999).

assessments of risk tolerance run the risk of suggesting inappropriate, and in the majority of cases overly conservative, investment strategies for their clients.

The analysis of the relationship between investor demographics and risk tolerance confirms the findings of the first study, that gender, income, age and wealth are significantly associated with financial risk tolerance. A detailed investigation of the relationship between risk tolerance and age suggests that a negative relationship between age and risk tolerance exists which, while in line with generally held industry beliefs, contradicts some of the more recent research findings. Further, the relationship between age and risk tolerance was found to exhibit a significant nonlinear structure. A negative relationship between risk tolerance and marital status was identified also.

Chapter 4 continues the analysis of the very large database of psychometrically-derived risk profiles of adult Australians aged between 20 and 80 years, and provides evidence that women differ from men in their attitude to financial risk taking. Regression analysis of risk tolerance scores (RTS) on the demographic characteristics of gender, marital status, number of dependents, age, education, income, combined income and net assets reveals each of these characteristics to be significant determinants of risk tolerance, with the first four characteristics having a negative relationship with RTS. The impact of gender was explored through dummy variable enhanced regression analysis constructed to test the increment in each demographic coefficient derived from being female relative to the base case of being male. Evidence of non-linearity in the relationships between RTS and demographic characteristics was also examined.

This study contributes to the literature by providing evidence that women do differ from men in their attitude to financial risk taking. This finding is based on the analysis of the database consisting of psychometrically-derived risk profiles for around 20,000 adult Australians. As much of the extant literature uses US data, our use of Australian data provides an important response to the concerns raised by Jiankoplos and Bernasek (1998) that much of what we know about investor risk tolerance could be country specific. As Australia shares a number of demographic and cultural similarities with other developed countries, we believe our results are relevant for these countries as well.

1.6.2. Supply Side Essays

Chapters 5 through 7 focus on risk shifting behavior by fund managers. Chapter 5 examines the market timing ability of a segment of the Australian investment fund industry, namely, equity trusts, over the period 1988 to 1997. The approach followed involves running both quadratic excess returns market model and dual-beta excess returns market model regressions. In addition, some specification tests are applied. The results suggest that for the sample over the period examined, there is little evidence of market timing ability. Further, there is no clear dominance of one market timing model over the other. The study finds however, that a cubic market model specification does fit the data quite well for nearly one third of the sample.

Chapter 6 builds on Taylor’s (2003) extension of the tournament model of Brown et al. (1996). Taylor (2003) proposes that using an exogenous (endogenous) benchmark will induce losing (winning) managers to gamble. This presents two competing testable hypotheses that are investigated in the current study. A non-parametric Cross-Product Ratio methodology is applied to a sample of Australian multi-sector growth funds covering the period 1989 to 2001. Generally, the study finds evidence in support of Taylor’s model. Specifically, when an exogenous benchmark is used the support is particularly evident for the Calendar-year analysis. Viewed as a whole, the analysis involving endogenous benchmarks is also quite supportive – particularly so for the Financial-year investigations (and to a lesser extent also with the Calendar-year results). Overall, the findings are consistent with the view that the Australian financial press and investors are particularly fixated on Financial and Calendar-year investment performance.

Chapter 7 further investigates the tournament induced risk-shifting behavior of Australian multi-sector growth funds. In this study a regression-based methodology is used to examine tournaments based on the calendar year, the financial year and an October-September year. Apart from the standard tournament hypothesis, the following hypotheses are explored: (a) a stability hypothesis; (b) a non-linearity hypothesis; (c) a fund age hypothesis; and (d) a fund size hypothesis. The findings can be summarized as follows. First, there is evidence in favour of the risk shifting tournament hypothesis when tournaments are defined with a September year end, but in the opposite direction for financial year end tournaments. Second, sub-period investigation revealed a strong pattern of less negative (more positive) association between interim performance and risk shifting for the September-based (Financial year) tournaments. Third, with regard to non-linearity, there are two cases with some prevalence: September year end tournaments tend to be typified by extreme losers (winners) who increasingly (decreasingly) chase high (low) risk and Financial year end tournaments tend to be typified by extreme losers (winners) who decreasingly (increasingly) chasing low (high) risk. Fourth, the analysis suggests that while fund age doesn't matter in either the September or Financial year end tournament scenarios, in the case of Calendar years the conventional tournament effect seems to be coming from the more established funds. In contrast, well-performing younger funds tend to chase higher risk. Finally, the 'fund size' hypothesis for (a) the September year tournaments suggests that, if anything, it is intermediate sized funds pursuing risk shifting tournament; (b) the Calendar year there is little evidence of risk shifting behaviour, regardless of fund size; (c) the Financial year there is a general tendency, regardless of fund size, toward positive risk shifting.

Chapter 8 presents the overall conclusions of the thesis, summarizes the major findings of the empirical analysis and contributions to the existing literature in finance, and indicates directions for future research.

Part A: Demand Side Studies

Chapter 2: An Exploratory Investigation of the Relation Between Risk Tolerance Scores and Demographic Characteristics[4]

2.1. Introduction

Financial risk tolerance is a term widely used in the personal financial planning industry to refer to an investor's attitude towards risk. It can be defined as the amount of uncertainty or investment return volatility that an investor is willing to accept when making a financial decision (Grable, 2000; Grable and Lytton, 1999) or the extent to which an individual is prepared to risk experiencing a less attractive outcome in the pursuit of a more attractive outcome (Davey, 2000). As such, financial risk tolerance may be considered to be the inverse of the concept of risk aversion that has played such a central role in financial economics. While risk tolerance and risk aversion may be considered to be two sides of the same coin, the former is generally considered to be more intuitive and, as such, a more relevant concept for use in communicating opinions about risk in the adviser-client context.

Risk tolerance is an important concept which has implications for both financial service providers and consumers. For the latter, risk tolerance is one factor which may determine the appropriate composition of assets in a portfolio which is optimal in terms of risk and return relative to the needs of the individual (Droms, 1987). In fact, the well-documented home country bias of investors may be a manifestation of risk aversion on the part of investors (see Cooper and Kaplanis, 1994 and Simons, 1999). For fund managers, Jacobs and Levy (1996) argue that the inability to effectively determine investor risk tolerance may lead to homogeneity among investment funds. Further, Schirripa and Tecotzky (2000) argue that the

---

[4] Parts of this chapter are drawn from a paper published by the candidate: Hallahan, T., Faff, R. and McKenzie, M. (2003). An Exploratory Investigation of the Relation between Risk Tolerance Scores and Demographic Characteristics, *Journa of Multinational Financial Management*, 13, 483-502

standard Markowitz portfolio optimisation process can be optimised by pooling groups of investors together with different attitudes to risk into a single efficient portfolio that maintains the groups average risk tolerance.

Despite its importance in the financial services industry, many unanswered questions exist with respect to the 'determinants' of risk tolerance.[5] Although a number of factors have been proposed and tested, a brief survey of the results reveals a distinct lack of consensus. First, it is generally thought that risk tolerance decreases with age (see Wallach and Kogan 1961; McInish 1982; Morin and Suarez 1983; and Palsson 1996) although this relationship may not necessarily be linear (see Riley and Chow 1992; Bajtelsmit and VanDerhai 1997). Intuitively this result can be explained by the fact that younger investors have a greater (expected) number of years to recover from the losses which may be incurred with risky investments. Interestingly, there is some suggestion that biological changes in enzymes due to the aging process may be responsible (see Harlow and Brown, 1990). More recent research however, finds evidence of a positive relationship or fails to detect any impact of age on risk tolerance (see Wang and Hanna 1997; Grable and Joo 1997; Grable and Lytton 1998, Hanna, Gutter and Fan, 1998; Grable 2000, Hariharan, Chapman and Domian, 2000; and Gollier and Zeckhauser, 2002).

A second demographic which is frequently argued to determine risk tolerance is gender and Bajtelsmit and Bernasek (1996), Palsson (1996), Jianakoplos and Bernasek (1998), Bajtelsmit, Bernasek and Jianakoplos (1999), Powell and Ansic (1997), Grable (2000), and Grable and Joo (2000) find support for the notion that females have a lower preference for risk than males. However, Grable and Joo (1999) and Hanna, Gutter and Fan (1998) find that

[5] The term 'determinants' is used to refer to the identification of factors/variables that reveal a strong and systematic association with risk tolerance.

gender is not significant in predicting financial risk tolerance, and Ackert, Church and Englis (2002) produced inconclusive results.

Education is a third factor which is thought to increase a person's capacity to evaluate risks inherent to the investment process and therefore endow them with a higher financial risk tolerance (see Baker and Haslem, 1974; Haliassos and Bertaut, 1995; Sung and Hanna, 1996). Shaw (1996) derives a model which suggests an element of circularity in this argument however, as the relative risk aversion of an individual is shown to determine the rate of human capital acquisition.

Income and wealth are two related factors which are hypothesised to exert a positive relationship on the preferred level of risk (see Friedman 1974; Cohn, Lewellen, Lease and Schlarbaum 1975; Blume 1978; Riley and Chow 1992; Grable and Lytton 1999; Schooley and Worden 1996; Shaw 1996; and Bernheim, Skinner and Weinberg 2001). For the latter, however, the issue is not clear cut. On the one hand, wealthy investors can more easily afford to incur the losses resulting from a risky investment and their accumulated wealth may even be a reflection of their preferred level of risk. Alternatively, wealthy people may be more conservative with their money while people with low levels of personal wealth may view risky investments as a form of lottery ticket and be more willing to bear the risk associated with such payoffs. This argument is analogous to Bowman's (1982) proposition that troubled firms prefer and seek risk.

Marital status has also been postulated to impact on financial risk tolerance, however, the exact nature of the relationship is not clear. One view asserts that single people are more risk tolerant than married individuals because they have less responsibilities than married people, particularly in respect to dependents, and face less social risk (that is, potential loss of esteem) when undertaking risky investments (Roszkowski, Snelbecker and Leimberg, 1993). On the other hand, it has also been suggested that married individuals have greater risk taking propensities because of a greater capacity to absorb unfavourable outcomes. The empirical research fails to provide any insights as to which of these competing theories may be valid. A number of studies have failed to identify any significant relationship between marital status and financial risk tolerance (McInish, 1982; Masters, 1989; Haliassos and Bertaut, 1995). As such, the relationship between marital status and risk tolerance is an issue that remains unresolved. [6]

The contribution of this study is to provide further evidence on the validity of these heuristics by examining the relationship between a psychometrically derived measure of subjective risk tolerance and responses to questions on eight demographic characteristics. Specifically, cross-sectional regression analysis is used to quantify the effect of the demographic characteristics on risk tolerance.

2.2. Measuring Financial Risk Tolerance

Risk tolerance, reflecting a person's attitude towards taking on risk, is a complex psychological concept. Jackson, Hourany and Vidmar (1992) contend that risk tolerance has four dimensions: financial, physical, social and ethical. Moreover, they find that there appears to be consistency in decision-making within, but not across, each of these dimensions. Callan and Johnson (2002) note that it has long been accepted in the field of social psychology (see, for example, Secord and Backman, 1964) that attitudes have two components: a spoken component comprising a person's beliefs and an unspoken component reflecting a person's feelings and emotions. Consequently, the measurement of financial risk tolerance needs to capture both these aspects of the attitudinal construct.

[6] Other factors which have been found to impact on risk tolerance and are not included in this study are: race (see Leigh, 1986; Jianakoplos and Bernasek, 1998; and Xiao, Alhabeeb, Gong-Soong and Haynes, 2000) the desire to leave an estate and expectations about the adequacy of pension income (see Schooley and Worden, 1996).

The three main methods for measuring financial risk tolerance involve one or a combination of: assessing actual behavior (Schooley and Worden, 1996, for example, find that portfolio allocations may be used to infer attitudes to risk); assessing responses to hypothetical scenarios and/or investment choices (see Barsky, Juster, Kimball and Shapiro, 1997 and Hey, 1999); and subjective questions (see Hanna, Gutter and Fan, 1998 for a survey of these different techniques).[7]

The use of the latter of these approaches – experimental questionnaire data – remains the primary method for assessing financial risk tolerance. However, because of the complexity of the attitudinal construct, a sophisticated psychological testing instrument is required to elucidate a person's attitude to financial risk.

Psychometrics is that area of psychology dealing with the design and analysis of measurements of human characteristics. Perhaps the most prominent example of psychometric testing is the Myers-Briggs Type Indicator, an attitudinal and personality test widely used in the recruitment and personnel areas. and Johnson (2002) provide an overview of the issues involved in constructing an appropriate psychometric instrument to measure financial risk tolerance. A good attitudinal test will meet accepted psychological standards for both face validity (perceived relevance of the questions) and predictive validity (prediction of later performance or behaviour), reliability (consistency in results for repeated tests of the same person), as well as having appropriate test norms so that subjects' test scores can be interpreted against an appropriate reference group.

FinaMetrica Ltd.[8] is an Australian company that uses such an approach to measure the preferred level of risk of an investor and have kindly provided the enlarged database to be

[7] An interesting alternative involves the use of insurance contracts to measure risk tolerance (Dreze, 1987).

[8] At the time the research was undertaken, FinaMetrica Ltd. operated under the name ProQuest Ltd.

analysed in our study. The FinaMetrica Personal Financial Profiling system is a proprietary, commercially provided computer-based risk tolerance measurement tool. It is a psychometric attitude test comprising 25 questions that generate a standardized Risk Tolerance Score (RTS) on a scale of 1 – 100, with higher scores indicating higher risk tolerance. The test, which has a univariate factor structure, has been subject to usability, reliability and norming trials by the University of New South Wales and has been found to have reliability statistics in excess of international psychometric standards. The test has been normed against a reference group of 5000 Australians.[9] Accompanying the risk tolerance test is a set of eight demographic questions requesting information on year of birth, gender, postcode, education, income, marital status, number of dependents and net assets. Details of the demographic questions are provided in Appendix 2.1. The FinaMetrica Personal Financial Profiling system is available commercially to the financial planning industry and can be completed in hard-copy form or accessed through the Internet.[10]

2.3. Data and Sampling

The data used in this exploratory study was made available by FinaMetrica. The sample provided comprised 3124 Australian respondents who completed the test in January – February 2002. Approximately 60 per cent of the respondents were identified as having completed the test in response to an invitation made to readers of Personal Investor magazine, 20 per cent of the respondents were identified as clients of financial advisers and the remainder was classified by FinaMetrica as non-specific. The Personal Investor readers completed the test by visiting the magazine's website where they could then access an internet link to the FinaMetrica website. Clients of financial advisers either completed the test online or completed a hard copy of the questionnaire sent to them in advance of meeting with their

[9] This information is available through the following link on the FinaMetrica web site: www.risk-profiling.com.
[10] See www.FinaMetrica.com.au for further information about the FinaMetrica system.

adviser. Following consultation with FinaMetrica, respondents who recorded their age as less than 20 years or older than 80 years, and respondents who generated a RTS outside the range 20-95 were omitted from the analysis, as such responses were not considered plausible. A group of 121 respondents were excluded on these criteria, leaving a sample of 3003, comprising 2105 males and 898 females.

As noted above, the FinaMetrica database furnishes details as to the respondent's gender, age, education, income, marital status, net assets, home state as well as their FinaMetrica Risk Tolerance Score (RTS hereafter). It is acknowledged that the sample is not a representative cross-section of society since it is primarily sourced from readers of Personal Investor magazine. These individuals however, may represent a cross section of people who seek investment and personal financial planning advice and so embody a reasonable cross-section of those in society who are likely to seek professional investment and personal financial planning advice.

Table 2.1 summarises the demographics data and the average survey participant was a 31 – 40 year old university educated married male who earns \$50,000 to \$100,000 and has net assets of \$150,000 to \$500,000. The atypical respondent was a 60+ year old low income unmarried female with less than \$50,000 in net assets who did not complete high school. Table 2.2 presents summary information of the risk tolerance score for each demographic sub grouping. The left hand side of each panel summarises the RTS for each demographic and the right hand side of each panel summarises the age (in years) for each demographic group. Panel A shows that the average RTS across the sample was 62.24. Males (64.39) exhibit a significantly greater tolerance for risk compared to females (57.18).[11] People who are unmarried (63.04) are more willing to bear risk compared to their married (62.04) counterparts, although this

[11] The ANOVA test for the equality of means is used in this paper at a 5% significance level.

difference is not statistically significant. The right hand side of Panel A reveals that the mean age of the survey respondents was 43.91 years and the average male survey participant (44.69 years) is significantly older than the average female (42.09 years). Finally, married respondents (46.20 years) were approximately ten years older compared to those who were unmarried (36.51).

Table 2.1 Summary of the FinaMetrica Dataset by Demographics

	Number of observations	% of sample
Panel A: Gender		
Males	2105	70%
Females	898	30%
Panel B: Age		
< 30 years old	580	19%
31-40 years old	715	24%
41-50 years old	686	23%
51-60 years old	688	23%
>60 years old	334	11%
Panel C: Education (highest qualification attained)		
Did not complete high school	164	5%
High School	375	12%
Trade/Diploma	661	22%
University	1803	60%
Panel D: Income		
< $30,000	485	16%
$30,000-$50,000	593	20%
$50,000-$100,000	1125	37%
$100,000-$200,000	553	18%
>$200,000	247	8%
Panel E: Marital status		
Married (incl. Defacto)	2280	76%
Unmarried	723	24%
Panel F: Net assets		
< $50,000	390	13%
$50,000-$150,000	416	14%
$150,000-$500,000	966	32%
$500,000-$1,000,000	660	22%
>$1,000,000	571	19%

Table 2.2 Risk Tolerance Score Summary

Panel A: Full sample/gender/marital Status

	Risk tolerance score					Age (years)				
	Full sample	Males	Females	Married	Unmarried	Full sample	Males	Females	Married	Unmarried
Mean	62.24	64.39	57.18	62.04	63.04	43.91	44.69	42.09	46.20	36.51
Median	62.00	64.00	57.00	62.00	64.00	44.00	44.00	42.00	46.00	31.00
Maximum	94.00	94.00	91.00	94.00	91.00	79.00	79.00	79.00	79.00	78.00
Minimum	22.00	23.00	22.00	22.00	23.00	21.00	21.00	21.00	21.00	21.00
Std. Dev.	12.24	11.62	12.17	12.19	12.27	13.16	13.10	13.13	12.05	13.87
Skewness	-0.18	-0.20	-0.05	-0.16	-0.26	0.16	0.15	0.18	0.13	0.80
Kurtosis	2.97	3.12	2.83	3.01	2.91	2.16	2.17	2.13	2.22	2.65

Panel B: Age-based subgroups

	Risk tolerance score					Age (years)				
Years	< 30	31-40	41-50	51-60	> 60	< 30	31-40	41-50	51-60	> 60
Mean	64.58	65.92	63.27	59.17	54.48	25.96	35.48	45.69	55.39	65.84
Median	65.00	66.00	63.00	59.00	55.00	26.00	36.00	46.00	55.00	64.00
Maximum	93.00	93.00	94.00	94.00	91.00	30.00	40.00	50.00	60.00	79.00
Minimum	26.00	31.00	23.00	22.00	23.00	21.00	31.00	41.00	51.00	61.00
Std. Dev.	11.78	11.63	10.98	12.41	11.47	3.02	2.84	2.82	2.77	4.68
Skewness	-0.23	-0.16	-0.23	-0.08	-0.1	-0.24	-0.03	-0.13	0.04	0.99
Kurtosis	3.07	2.65	3.58	2.92	2.87	1.70	1.79	1.86	1.9	3.12

Panel C: Education-based subgroups

	Risk tolerance score				Age (years)			
Education								
	DNC*	High Sch.	Trade/Dip	University	DNC*	High Sch.	Trade/Dip	University
Mean	57.58	58.13	60.83	64.10	50.82	46.05	47.39	41.53
Median	58.00	58.00	61.00	64.00	54.00	48.00	48.00	40.00
Maximum	91.00	92.00	94.00	94.00	76.00	79.00	79.00	79.00
Minimum	23.00	23.00	22.00	25.00	22.00	21.00	21.00	21.00
Std. Dev.	14.04	13.03	12.62	11.29	12.85	13.45	12.70	12.70
Skewness	-0.12	-0.07	-0.08	-0.12	-0.29	-0.16	-0.01	0.33
Kurtosis	2.45	2.78	2.99	2.95	2.13	2.29	2.21	2.27

Panel D: Income-based subgroups

Income Band	Risk tolerance score < $30,000	$30,000-$50,000	$50,000-$100,000	$100,000-$200,000	>$200,000	Age (years) < $30,000	$30,000-$50,000	$50,000-$100,000	$100,000-$200,000	>$200,000
Mean	55.42	60.69	63.84	66.41	64.68	45.05	43.43	43.28	44.13	45.84
Median	56.00	61.00	64.00	66.00	65.00	48.00	43.00	43.00	44.00	46.00
Maximum	92.00	91.00	94.00	93.00	94.00	79.00	79.00	78.00	78.00	78.00
Minimum	22.00	23.00	23.00	35.00	31.00	21.00	21.00	21.00	22.00	22.00
Std. Dev.	12.54	11.85	11.46	10.64	11.84	16.75	14.92	12.01	10.42	9.60
Skewness	0.01	-0.16	-0.06	-0.05	-0.17	-0.07	0.19	0.26	0.31	0.09
Kurtosis	2.74	2.98	3.05	2.90	2.87	1.69	1.89	2.20	2.39	2.82

Panel E: Net assets-based subgroups

N.A. Band	Risk tolerance score < $50,000	$50,000-$150,000	$150,000-$500,000	$500,000-$1,000,000	>$1,000,000	Age (years) < $50,000	$50,000-$150,000	$150,000-$500,000	$500,000-$1,000,000	>$1,000,000
Mean	62.23	64.93	61.99	61.68	62.52	27.89	35.26	44.01	50.01	53.01
Median	63.00	66.00	62.00	62.00	62.00	26.00	32.00	43.00	50.00	54.00
Maximum	93.00	91.00	93.00	94.00	94.00	60.00	78.00	79.00	79.00	78.00
Minimum	26.00	23.00	22.00	28.00	28.00	21.00	21.00	21.00	21.00	22.00
Std. Dev.	11.65	12.97	12.60	11.50	11.61	7.56	10.21	11.47	10.35	9.65
Skewness	-0.10	-0.42	-0.29	0.04	-0.03	1.87	1.34	0.46	0.09	-0.23
Kurtosis	3.17	3.15	2.97	2.81	2.89	6.62	4.88	2.56	2.61	2.96

Note: * - did not complete high school.

Panel B of Table 2.2 shows that the highest average RTS is exhibited by the 31 – 40 year age group (65.92). Most interestingly, the relationship between the willingness to bear risk and age appears to be nonlinear. The average RTS increases as people reach their 30's most likely as a result of individuals gaining confidence and experience in the investment process. As people enter their 40's however, they become more conservative and their willingness to bear risk declines at an increasing rate. The right hand side of Panel B presents the average age within each age sub grouping. The mean age falls very close to the middle of each sub grouping (ie. in the 31 – 40 subgroup, the mean age was 35.48 years) and the descriptive statistics are very similar across all subgroups. This gives confidence that the distribution of our sample respondents is consistent across the spectrum of ages and so the results are unlikely to be driven by the occurrence of outliers or a lack of observations in a particular grouping.

Panel C presents the RTS classified by education level and as is to be expected, the more educated a person is, the greater their willingness to bear risk. The mean age within each education level sub grouping reveals an interesting trend as those who did not finish high school (50.82 years) were on average significantly older compared to respondents who had completed university (41.53 years). This is consistent with the general trend towards higher levels of education in Australian society and more people finishing school.

The average RTS of survey participants categorised by their personal income (Panel D) shows that peoples' attitudes to risk differ across income levels. More specifically, for income brackets up to $200,000, average RTS and income display positive correlation. One possible interpretation of this finding is that individuals with higher incomes are better able to absorb, and are therefore more tolerant of, investment return variability. However, reported personal income in excess of $200,000 displays an average RTS somewhat lower than the RTS for the

\$100-\$200,000 income group. It could be argued that this cross-sectional concavity in the income-RTS relationship is consistent with the economic concept of diminishing marginal utility of money - the more money people have, the less value they place on an additional dollar of income. From Panel D, it would appear that individuals with an income in excess of \$200,000 are willing to settle for a lower risk/return compared to those with an income of \$100,000 to \$200,000. One could speculate that this may be because they value the potential additional investment returns less because of their lower marginal utility of money.

Panel E presents the RTS categorised by Net Assets and the mean RTS is similar across all levels of asset holdings, except for the \$50,000 - \$150,000 which is significantly higher. Thus, individuals who have accumulated this level of assets are significantly different from all other holders of net assets as they are willing to take on higher levels of risk.

2.4. Modelling the Determinants of Risk Tolerance

In order to test the determinants of risk tolerance, a number of different demographic factors may be considered. The data collected from the Personal Investor Magazine survey provides information as to gender, age, education, marital status, number of dependents, personal income, combined family income and net assets. [This demographic data is collected as part of the FinaMetrica Risk Profiling process.] It is possible to quantify the effect of each of these demographic characteristics on the risk tolerance of an individual using statistical analysis. The model to be tested in this paper hypothesises that the RTS for individual i is a function of each of these demographic characteristics, ie.:

$$
\begin{aligned}
RTol_i = {} & \alpha_0 + \alpha_1 D_{i,FEM} + \alpha_2 AGE_i + \alpha_3 NDEP_i + \alpha_4 D_{i,MARRIED} + \\
& \sum_{g=EDU_2}^{EDU_4} \alpha_g D_{i,g} + \sum_{h=INC_2}^{INC_5} \alpha_h D_{i,h} + \sum_{j=CINC_2}^{CINC_5} \alpha_j D_{i,j} + \sum_{k=NASS_2}^{NASS_5} \alpha_k D_{i,k} + \varepsilon_i
\end{aligned} \tag{2.1}
$$

where $RTol_i$ is the financial risk tolerance score for individual *i* provided by FinaMetrica based on the answers to their Risk Tolerance Questionnaire and takes a value of zero to 100 and;

D_{FEM} is a dummy variable that signifies a respondent is female;

AGE is the age of the respondent (in whole years);

NDEP is the number of people in the family whom are financially dependent on the respondent;

$D_{MARRIED}$ is a dummy variable that takes a value of unity if the respondent is married (legally or defacto);

D_{EDU} captures the completed level of education of the respondent and includes did not complete high school (D_{EDU1}), completed high school (D_{EDU2}), trade/diploma (D_{EDU3}), or university (D_{EDU4}) level education;

D_{INC} shows the respondent's income as, < \$30,000 (D_{INC1}), \$30,000 - \$50,000 (D_{INC2}), \$50,000-\$100,000 (D_{INC3}), \$100,000-\$200,000 (D_{INC4}) or > \$200,000 (D_{INC5});

D_{CINC} indicates if the respondent's combined family income is, <\$30,000 (D_{CINC1}), \$30,000 - \$50,000 (D_{CINC2}), \$50,000-\$100,000 (D_{CINC3}), \$100,000-\$200,000 (D_{CINC4}), or > \$200,000 (D_{CINC5});

D_{NASS} takes a value of unity if the respondent's net assets are <\$50,000 (D_{NASS1}), \$50,000 - \$150,000 (D_{NASS2}), \$150,000-\$500,000 (D_{NASS3}), \$500,000-\$1,000,000 (D_{NASS4}) or > \$1,000,000 (D_{NASS5}).

This model may be estimated using cross-sectional regression analysis and results are presented in Table 2.3. The constant term in this model captures the omitted case which is an unqualified male with a personal and family income of less than \$30,000 and net assets of less than \$50,000. The RTS for this representative individual is 68.77 and the RTS for individuals who differ from our base case can be assessed by considering the significance and sign of the estimated coefficients in the model. Gender is a significant determinant of risk tolerance and a female will exhibit a RTS of 6.8 points less compared to a demographically equivalent male. Similarly, age is also a significant determinant of the RTS and risk tolerance declines around 3 score points for every passing decade.

Table 2.3 Regression of Financial Risk Tolerance Score on Demographic Variables

Variable	Coefficient	Std. error	t-statistic	Prob.
α	68.7765	2.20	31.28	0.000
D_{FEM}	-6.8714	0.59	-11.66	0.000
AGE	-0.3101	0.03	-12.27	0.000
NDEP	-0.1413	0.17	-0.81	0.417
$D_{MARRIED}$	-0.7449	1.64	-0.45	0.650
D_{EDU2}	-1.2268	1.17	-1.05	0.295
D_{EDU3}	-0.9134	1.08	-0.85	0.398
D_{EDU4}	0.5431	1.04	0.52	0.603
D_{INC2}	2.8231	0.95	2.97	0.003
D_{INC3}	3.7074	1.00	3.73	0.000
D_{INC4}	4.8002	1.21	3.98	0.000
D_{INC5}	2.8078	1.69	1.66	0.097
D_{CINC2}	3.6509	1.43	2.56	0.011
D_{CINC3}	3.0035	1.44	2.09	0.037
D_{CINC4}	3.4428	1.55	2.22	0.027
D_{CINC5}	3.4002	1.84	1.85	0.064
D_{NASS2}	3.8825	1.20	3.23	0.001
D_{NASS3}	3.8952	1.14	3.42	0.001
D_{NASS4}	4.4567	1.24	3.60	0.000
D_{NASS5}	5.4596	1.34	4.09	0.000

Adjusted R-squared = 0.2134 DW = 1.91 F-stat = 31.58 (P-value = 0.000)

Wald Tests of Coefficient Equality :	($D_{INC2} = D_{INC3} = D_{INC4} = D_{INC5}$)	P-value = 0.125
	($D_{INC4} = D_{INC5}$)	P-value = 0.117
	($D_{CINC2} = D_{CINC3} = D_{CINC4} = D_{CINC5}$)	P-value = 0.849
	($D_{NASS2} = D_{NASS3} = D_{NASS4} = D_{NASS5}$)	P-value = 0.191
	($D_{NASS4} = D_{NASS5}$)	P-value = 0.154

The dependent variable of this regression is the financial risk tolerance score for individual *i* provided by FinaMetrica based on the answers to their Risk Tolerance Questionnaire and takes a value of zero to 100. The independent variables are defined as follows: D_{FEM} is a dummy variable that signifies a respondent is female; AGE is the age of the respondent (in whole years); NDEP is the number of people in the family whom are financially dependent on the respondent; $D_{MARRIED}$ is a dummy variable that takes a value of unity if the respondent is married (legally or defacto); D_{EDU} captures the completed level of education of the respondent and includes did not complete high school (D_{EDU1}), completed high school (D_{EDU2}), trade/diploma (D_{EDU3}), or university (D_{EDU4}) level education; D_{INC} shows the respondent's income as, < \$30,000 (D_{INC1}), \$30,000 - \$50,000 (D_{INC2}), \$50,000-\$100,000 (D_{INC3}), \$100,000-\$200,000 (D_{INC4}) or > \$200,000 (D_{INC5}); D_{CINC} indicates if the respondent's combined family income is, <\$30,000 (D_{CINC1}), \$30,000 - \$50,000 (D_{CINC2}), \$50,000-\$100,000 (D_{CINC3}), \$100,000-\$200,000 (D_{CINC4}), or > \$200,000 (D_{CINC5}); D_{NASS} takes a value of unity if the respondent's net assets are <\$50,000 (D_{NASS1}), \$50,000 - \$150,000 (D_{NASS2}), \$150,000-\$500,000 (D_{NASS3}), \$500,000-\$1,000,000 (D_{NASS4}) or > \$1,000,000 (D_{NASS5}).

The series of dummy variables capturing the level of income of an individual (D_{INC}) were all individually significant and positive as were the combined family income (D_{CINC}) and net asset (D_{NASS}) dummy variables.[12] The estimated results indicate that the RTS of an individual generally increases as income and assets increase however, this effect does not appear to be uniform. More specifically, a combined family income of >$30,000 is found to add approximately 3 points to the RTS as the estimated coefficient for $D_{CINC2\text{-}5}$ ranges from 3.00 to 3.65. A Wald test of coefficient equality fails to reject the null hypothesis $D_{CINC2} = D_{CINC3} = D_{CINC4} = D_{CINC5}$ at the 10% level. The estimated coefficients for the $D_{INC2\text{-}5}$ and $D_{NASS2\text{-}5}$ series of dummy variables however, are less uniform. For the former, higher levels of income are found to be associated with successively higher RTS except for the top income bracket. Although the increment to the RTS over the base case is still positive ($D_{INC5} = 2.80$), it is less than that found for the income bracket preceding it ($D_{INC4} = 4.80$). A Wald test of coefficient equality between D_{INC5} and D_{INC4} generates a P-value of 0.11. A similar pattern is exhibited by the dummy variables capturing net assets and a Wald test of the equality of the $D_{NASS4} = D_{NASS5}$ variables generates a P-value of 0.15.

Not all of the demographic characteristics tested in equation (2.1) were found to be significant. The level of education of an individual, their marital status and the number of dependents were all found to be insignificant in determining the RTS of our sample group.

2.5. The Relationship Between Risk Tolerance and Age

The model specified in equation (2.1) specifies a monotonic relationship between age and RTS. It is possible that the RTS may decline geometrically with age however, and to test this hypothesis, age may be partitioned into a series of arbitrarily determined dummy variables. More specifically, five sub groupings were created which take on a value of unity where the

[12] The D_{CINC5} variable was significant at the 10% level.

respondents age is 18 – 30 (D_{AGE1}), 31 to 40 (D_{AGE2}), 41 to 50 (D_{AGE3}), 51 to 60 (D_{AGE4}) or greater than 60 years (D_{AGE5}). Thus a modified version of equation (2.1) may be tested which takes the form:

$$
\begin{aligned}
RTol_i = \alpha_0 + \alpha_1 D_{i,FEM} + \sum_{f=AGE_2}^{AGE_5} \alpha_f D_{i,f} + \alpha_3 NDEP_i + \alpha_4 D_{i,MARRIED} + \\
\sum_{g=EDU_2}^{EDU_4} \alpha_g D_{i,g} + \sum_{h=INC_2}^{INC_5} \alpha_h D_{i,h} + \sum_{j=CINC_2}^{CINC_5} \alpha_j D_{i,j} + \sum_{k=NASS_2}^{NASS_5} \alpha_k D_{i,k} + \varepsilon_i
\end{aligned}
\tag{2.2}
$$

where all variables are defined as per equation (2.1). In this revised model, the base case becomes an unqualified male who is less than 30 years of age, with a personal and family income of less than \$30,000 and net assets of less than \$50,000. The estimation results of this model are presented in Table 2.4 and excluding the series of dummy variables capturing age, the same pattern of coefficient signs and significance are observed in this revised model. In terms of the age dummy variables, the 31 to 40 age grouping generally exhibits a 1.6 point lower RTS which is significant at the 10% level. For the remaining age subgroups, the average RTS is significantly less than that of the base case and most importantly decreases at an increasing rate. A Wald test of the equality of the estimated age dummy variable coefficients clearly rejects the null hypothesis of equality. Thus, the evidence presented by this model suggests that the decline of the RTS as age increases is not linear.

Table 2.4 Regression of Financial Risk Tolerance Score on Demographic Variables (Age is Discrete)

Variable	Coefficient	Std. error	t-statistic	Prob.
α_0	60.4675	2.02	29.93	0.000
D_{FEM}	-6.8307	0.59	-11.52	0.000
D_{AGE2}	-1.6245	0.91	-1.79	0.074
D_{AGE3}	-4.1182	0.98	-4.20	0.000
D_{AGE4}	-7.6958	1.00	-7.71	0.000
D_{AGE5}	-11.3967	1.16	-9.79	0.000
NDEP	-0.2201	0.19	-1.18	0.238
$D_{MARRIED}$	-1.1606	1.65	-0.70	0.481
D_{EDU2}	-1.1928	1.18	-1.01	0.310
D_{EDU3}	-0.7867	1.08	-0.73	0.467
D_{EDU4}	0.7038	1.05	0.67	0.502
D_{INC2}	2.8673	0.95	3.01	0.003
D_{INC3}	3.7531	1.00	3.76	0.000
D_{INC4}	4.8817	1.21	4.03	0.000
D_{INC5}	2.9232	1.69	1.72	0.085
D_{CINC2}	3.6648	1.43	2.56	0.011
D_{CINC3}	3.0742	1.45	2.13	0.034
D_{CINC4}	3.5313	1.56	2.26	0.024
D_{CINC5}	3.4308	1.85	1.86	0.063
D_{NASS2}	3.3860	1.21	2.79	0.005
D_{NASS3}	3.0519	1.17	2.60	0.009
D_{NASS4}	3.4516	1.27	2.72	0.007
D_{NASS5}	4.4914	1.35	3.33	0.001

Adjusted R-squared = 0.2104 DW = 1.91 F-stat = 26.75 (P-value = 0.000)

Wald Tests of Coefficient Equality : ($D_{AGE2} = D_{AGE3} = D_{AGE4} = D_{AGE5}$) P-value = 0.000

The dependent variable of this regression is the financial risk tolerance score for individual *i* provided by FinaMetrica based on the answers to their Risk Tolerance Questionnaire and takes a value of zero to 100. The independent variables are defined as follows: D_{FEM} is a dummy variable that signifies a respondent is female; D_{AGE} captures the age of the respondent in discrete groups and includes age is: 18 – 30 (D_{AGE1}), 31 to 40 (D_{AGE2}), 41 to 50 (D_{AGE3}), 51 to 60 (D_{AGE4}) or greater than 60 years (D_{AGE5}); NDEP is the number of people in the family whom are financially dependent on the respondent; $D_{MARRIED}$ is a dummy variable that takes a value of unity if the respondent is married (legally or defacto); D_{EDU} captures the completed level of education of the respondent and includes did not complete high school (D_{EDU1}), completed high school (D_{EDU2}), trade/diploma (D_{EDU3}), or university (D_{EDU4}) level education; D_{INC} shows the respondent's income as, < \$30,000 (D_{INC1}), \$30,000 - \$50,000 (D_{INC2}), \$50,000-\$100,000 (D_{INC3}), \$100,000-\$200,000 (D_{INC4}) or > \$200,000 (D_{INC5}); D_{CINC} indicates if the respondent's combined family income is, <\$30,000 (D_{CINC1}), \$30,000 - \$50,000 (D_{CINC2}), \$50,000-\$100,000 (D_{CINC3}), \$100,000-\$200,000 (D_{CINC4}), or > \$200,000 (D_{CINC5}); D_{NASS} takes a value of unity if the respondent's net assets are <\$50,000 (D_{NASS1}), \$50,000 - \$150,000 (D_{NASS2}), \$150,000-\$500,000 (D_{NASS3}), \$500,000-\$1,000,000 (D_{NASS4}) or > \$1,000,000 (D_{NASS5}).

Further evidence as to the potential nonlinear relationship between age and the RTS may be ascertained by testing a quadratic model. To restrict the focus of this model, only the RTS and age (expressed as a continuous variable) are considered and as such, the model to be tested takes the form:

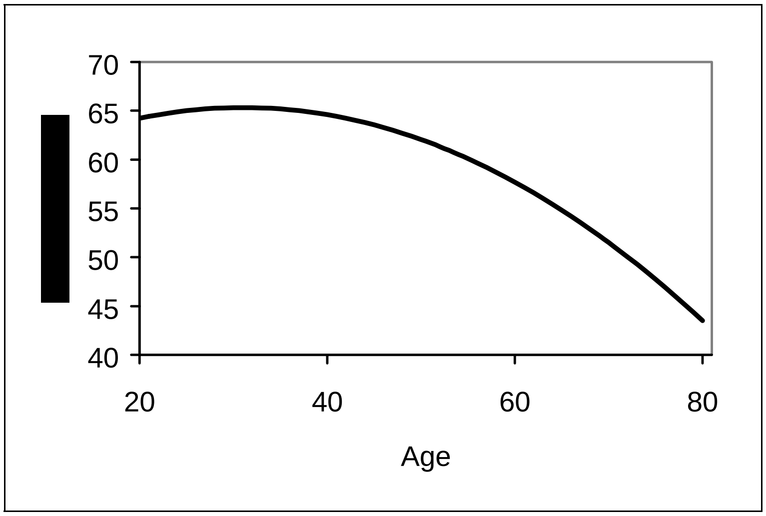
$$RTol_i = \beta_0 + \beta_1 Age_i + \beta_2 Age_i^2 + \varepsilon_i \tag{2.3}$$

The estimated regression results are presented in Table 2.5. The significance of all of the estimated coefficients provides clear evidence of nonlinear effects in the relationship between age and RTS, which reinforces the evidence of equation (2.2). A better understanding of this nonlinearity may be obtained using the estimated coefficients of equation (2.3). Figure 2.1 presents a plot of the predicted RTS for each year of age and the nonlinearity is clearly evident.

Table 2.5 Regression of Financial Risk Tolerance Score on Demographic Variables with Quadratic Age (Continuous Variable)

Variable	Coefficient	Std. error	t-statistic	Prob.
β	56.5749	2.25	25.17	0.000
AGE	0.5646	0.10	5.40	0.000
AGE^2	-0.0091	0.00	-7.92	0.000
Adjusted R-squared = 0.0885	DW = 1.901	F-stat = 154.51 (P-value = 0.000)		

Figure 2.1 Plot of Predicted Risk Tolerance Score Across Age from Quadratic Model



Thus, our results confirm the basic proposition that as people get older, their risk tolerance declines at an increasing rate. While the standard discounting argument can be used to justify this observation, the more recent literature provides an interesting alternative hypothesis, which suggests that biological changes in enzymes due to the aging process may be responsible (Harlow and Brown 1990).

In addition to nonlinearity in the relationship between age and RTS, it is possible that other similar effects may be present in the data. For example, there may be some form of interrelationship between wealth and age that has not been taken into account in the models tested so far. To investigate this matter further, the interrelationship between age and sole and family income as well as wealth was investigated and significant effects were found to be associated with incomes and net assets. A parsimonious model that focuses on these interrelationships may be specified as:

$$\begin{aligned} RTol_i = \chi_0 + \chi_1 D_{i,FEM} + \chi_2 AGE_i + \sum_{h=INC_2}^{INC_5} \chi_h D_{i,h} + \chi_3 D_{i,CINC_5} + \chi_4 D_{i,NASS_1} \\ + \chi_5 D_{i,CINC_5} AGE_i + \chi_6 D_{i,NASS_1} AGE_i + \varepsilon_i \end{aligned} \tag{2.4}$$

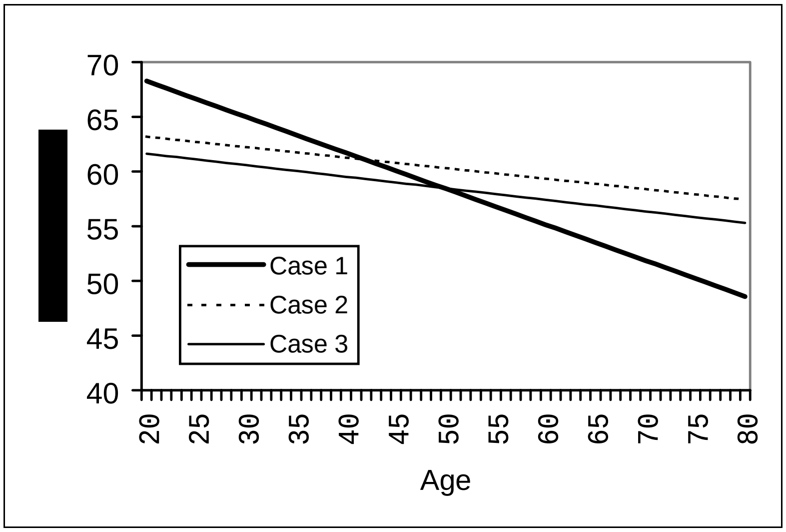
The estimated output for equation (2.4) is presented in Table 2.6 and an interpretation of this output suggests that high income (D_{CINC5}) or low net assets (D_{NASS1}) impact on the base case (ie. the constant), but also the relationship between age and RTS (ie. the slope). Specifically, the decline in RTS as age increases is lessened for those individuals that fall into these two extreme sub groupings. Figure 2.2 presents a plot of the relationship between RTS and age for the base case as suggested by the estimates presented in Table 2.6. The impact of the D_{CINC5} and D_{NASS1} variables on this relationship are also presented in Figure 2.2 and the change in the slope generated by the two significant coefficients is clearly visible. Thus, in addition to the nonlinearities which exist between age and RTS, evidence is also present to suggest that this relationship changes for high income and low asset individuals.

Table 2.6 Parsimonious Regression of Financial Risk Tolerance Score on Demographic Variables Interacting with Age (Continuous Variable)

Variable	Coefficient	Std. error	t-statistic	Prob.
χ	74.8115	1.37	54.47	0.000
D_{FEM}	-6.7579	0.56	-11.87	0.000
AGE	-0.3279	0.02	-15.02	0.000
D_{INC2}	3.9068	0.82	4.73	0.000
D_{INC3}	4.9277	0.75	6.50	0.000
D_{INC4}	6.6933	0.87	7.61	0.000
D_{INC5}	4.2842	1.48	2.88	0.003
D_{CINC5}	-9.7001	3.07	-3.15	0.001
D_{NASS1}	-11.071	3.86	-2.86	0.004
D_{CINC5}*AGE	0.2319	0.06	3.49	0.000
D_{NASS1}*AGE	0.2223	0.11	1.85	0.063
Adjusted R-squared = 0.2091		DW = 1.908	F-stat = 46.101 (P-value = 0.000)	

The dependent variable of this regression is the financial risk tolerance score for individual *i* provided by FinaMetrica based on the answers to their Risk Tolerance Questionnaire and takes a value of zero to 100. The independent variables are defined as follows: D_{FEM} is a dummy variable that signifies a respondent is female; AGE is the age of the respondent (in whole years); D_{INC} shows the respondent's income as \$30,000 - \$50,000 (D_{INC2}), \$50,000-\$100,000 (D_{INC3}), \$100,000-\$200,000 (D_{INC4}) or > \$200,000 (D_{INC5}); D_{CINC} indicates if the respondent's combined family income as > \$200,000 (D_{CINC5}); D_{NASS} takes a value of unity if the respondent's net assets are <\$50,000 (D_{NASS1}).

Figure 2.2 Plot of Predicted Risk Tolerance Score Across Age for Three Different Representative Cases



Note: This Figure displays three illustrative cases from the regression equation estimated for Table 2.6. ‘Case 1’ is a male with an income of < \$30,000; a combined family income of < \$200,000; and net assets of >\$50,000. ‘Case 2’ is the same as Case 1 except that the combined family income is > \$200,000. ‘Case 3’ is the same as Case 1 except net assets are less than \$50,000.

2.6. Risk Tolerance and Wealth

Section 2.5 clearly establishes age as an important determinant of an individual’s attitude to risk. The evidence presented in section 2.4 however, also suggests that income and wealth are important determinants. To investigate the influence of these factors on the RTS, a parsimonious version of equation (2.1) may be estimated in which only the most salient features of equation (2.1) are retained. From the discussion in section 2.4, gender, age, income and net wealth are important determinants of the RTS. The Wald tests of combined family income suggests that the effect of a family income of greater than \$30,000 on RTS are uniform and as such may be incorporated into the base case. Thus, D_{CINC_1} is included in the model and the model to be tested may be specified as:

$$RTol_i = \phi_0 + \phi_1 D_{i,FEM} + \phi_2 AGE_i + \sum_{h=INC_2}^{INC_5} \phi_h D_{i,h} + \phi_3 D_{i,CINC_1} + \sum_{k=NASS_2}^{NASS_5} \phi_k D_{i,k} + \varepsilon_i \qquad (2.5)$$

The estimation results of this parsimonious model are presented in Table 2.7 and all of the estimated coefficients are significant and retain their sign compared to their counterparts presented in Table 2.3.

Table 2.7 Parsimonious Regression of Financial Risk Tolerance Score on Demographic Variables

Variable	Coefficient	Std. error	t-statistic	Prob.
ϕ	71.2458	1.49	47.80	0.000
D_{FEM}	-6.7593	0.56	-12.03	0.000
AGE	-0.3153	0.02	-13.16	0.000
D_{INC2}	2.8807	0.93	3.09	0.002
D_{INC3}	3.9814	0.86	4.58	0.000
D_{INC4}	5.4870	0.97	5.62	0.000
D_{INC5}	3.4938	1.19	2.91	0.003
D_{CINC1}	-2.9650	1.29	-2.28	0.022
D_{NASS2}	3.6536	1.19	3.06	0.002
D_{NASS3}	3.5141	1.11	3.15	0.001
D_{NASS4}	4.1513	1.21	3.42	0.000
D_{NASS5}	5.1597	1.30	3.96	0.000
Adjusted R-squared = 0.2020		DW = 1.901	F-stat = 71.57 (P-value = 0.000)	

The dependent variable of this regression is the financial risk tolerance score for individual *i* provided by FinaMetrica based on the answers to their Risk Tolerance Questionnaire and takes a value of zero to 100. The independent variables are defined as follows: D_{FEM} is a dummy variable that signifies a respondent is female; AGE is the age of the respondent (in whole years); D_{INC} shows the respondent's income as, < \$30,000 (D_{INC1}), \$30,000 - \$50,000 (D_{INC2}), \$50,000-\$100,000 (D_{INC3}), \$100,000-\$200,000 (D_{INC4}) or > \$200,000 (D_{INC5}); D_{CINC} indicates if the respondent's combined family income is, <\$30,000 (D_{CINC1}), D_{NASS} takes a value of unity if the respondent's net assets are \$50,000 - \$150,000 (D_{NASS2}), \$150,000-\$500,000 (D_{NASS3}), \$500,000-\$1,000,000 (D_{NASS4}) or > \$1,000,000 (D_{NASS5}).

One advantage of this parsimonious model is that it is relatively easy to estimate a matrix which shows the RTS for males and females as age and income varies. Table 2.8 provides this information and Figures 2.3 and 2.4 provide a plot of this data to aid in the interpretation.

Table 2.8 Predicted Financial Risk Tolerance Scores from Parsimonious Model (of Table 2.7) – Combined Income > $30,000 and Net Assets < $1 million

Income ($000s)	Age (years) 25	30	35	40	45	50	55	60	65	70
Panel A: Males										
< 30	63	62	60	59	57	55	54	52	51	49
30 – 50	66	65	63	62	60	58	57	55	54	52
50 – 100	67	66	64	63	61	59	58	56	55	53
100 – 200	69	67	66	64	63	61	59	58	56	55
>200	67	65	64	62	61	59	57	56	54	53
Panel B: Females										
< 30k	57	55	53	52	50	49	47	46	44	42
30 – 50	59	58	56	55	53	52	50	48	47	45
50 – 100	61	59	57	56	54	53	51	50	48	46
100 – 200	62	61	59	57	56	54	53	51	49	48
>200	60	59	57	55	54	52	51	49	47	46

Note : The base case from the parsimonious model of Table 2.7 is a male with an income below $30,000, a combined family income of more than $30,000 and net assets of less than $50,000. The predicted financial risk tolerance score in this table can be converted to the case of:

(a) a family income less than $30,000 by deducting 3 index points
(b) net assets of between $50,000 and $500,000 by adding 3 index points
(c) net assets of between $500,000 and $1 million by adding 4 index points.
(d) net assets of greater than $1 million by adding 5 index points.

The figures provide a neat graphical interpretation of the lessons highlighted by the earlier models with respect to gender and age. The surface for women lay entirely below the surface for men reflecting their general lower level of tolerance for risk. Further, the downward slope of the surfaces reflects the decline in risk tolerance with age. An interesting feature of these surfaces is their concavity with respect to income. As income increases, the RTS of both men and women increases until the top income bracket where the average RTS declines somewhat irrespective as to age or gender. This suggests that individuals whose income exceeds $200,000, are more concerned with the security of their investments compared to those earning $100,000 to $200,000. This is an interesting result and suggests that the very wealthy in society are more cautious with respect to investment possibly as they are more concerned with protecting their wealth rather than increasing it.

Figure 2.3 Male Predicted Financial Risk Tolerance Scores from Parsimonious Model (Table 2.7)

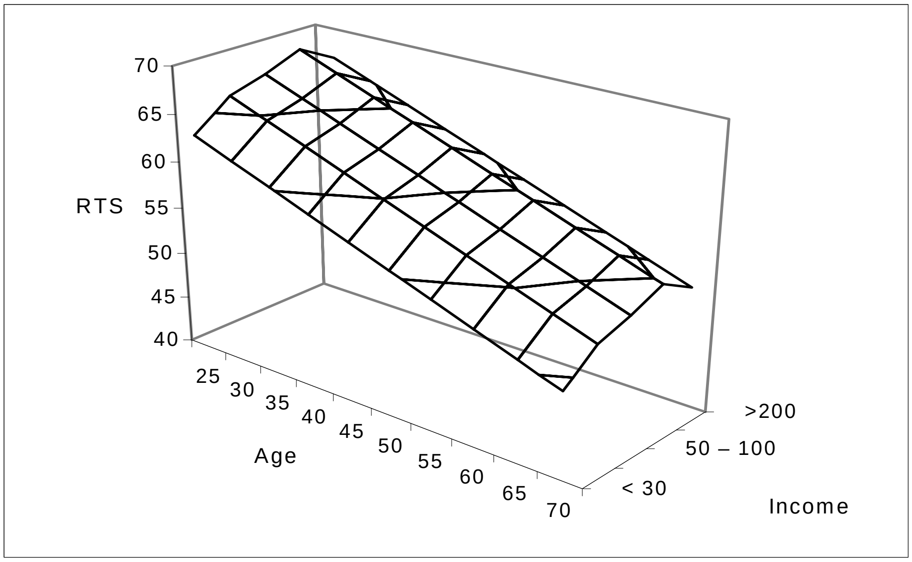
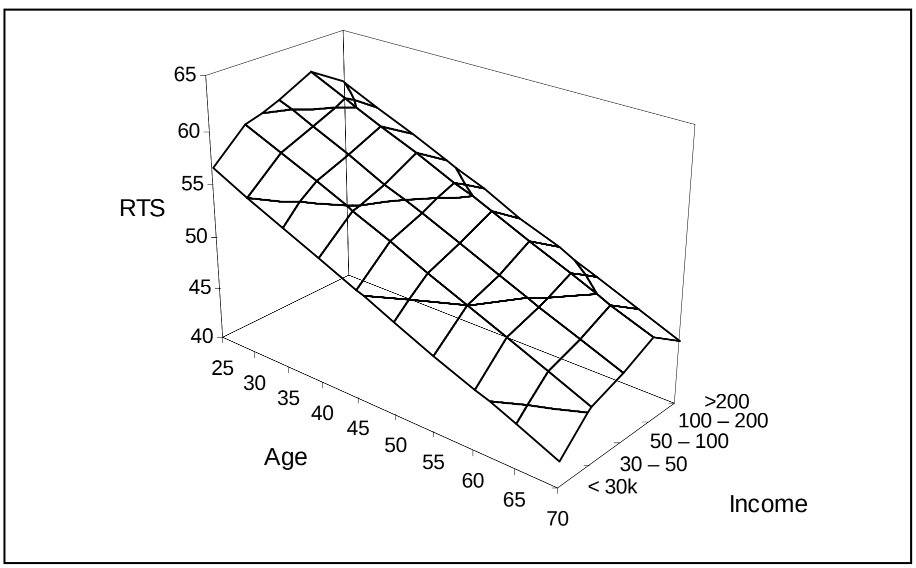


Figure 2.4 Female Predicted Financial Risk Tolerance Scores from Parsimonious Model (Table 2.7)



2.7. Conclusion

The FinaMetrica Personal Financial Profiling system has provided an opportunity to undertake a large sample examination of the relationship between subjective risk tolerance and demographic factors. While the sample group is not representative of the population at large, it is representative of those individuals likely to be active investors. The analysis provides insight into the effect of certain demographic characteristics on individuals' attitudes towards risk. The validity of widely used demographics such as gender, age, income and wealth as determinants of risk tolerance is supported, although the relationships found are not as simple as implied by the demographic heuristics. The R^2 values for the regressions, most of which are in the range 0.2-0.3, can be interpreted as evidence that variations in demographic characteristics, while relevant, are unable to fully explain variations in financial risk tolerance. Risk tolerance exhibits a concave relationship with income across all age groups, and irrespective of gender.

It is interesting to note that education, marital status and dependents, which have been found to be significant in previous studies, were not found to be significant determinants of an individual's attitude towards risk in this study. Accordingly, this finding is the subject of further examination, using a much larger sample, in Chapter 3.

Appendix 2.1 ProQuest Demographic Questionnaire

Personal Financial Profiling

Introduction

Many financial decisions are made in situations of uncertainty, and so risk is involved. Different people are comfortable with different levels of risk. A person's risk tolerance is the level of risk with which he or she is comfortable.

The whole issue of risk is a difficult one. Risk aversion prevents many of us doing as well as we might financially. Yet some of life's most unpleasant financial surprises arise because we were exposed to a level of risk beyond our comfort zone. It can be equally disappointing to miss an opportunity because someone else wrongly assumed we would not be willing to take the risk involved.

Unlike, say, height or weight, there is no unit of measurement for risk tolerance. A person's risk tolerance can only be measured relative to others on a constructed scale, in much the same way as IQ is measured. Additionally, even the meaning of "risk" can depend on the situation. When individuals talk about "risk" as they experience it in their personal financial affairs they are not talking about the same thing as, for example, investment researchers discussing the "risk" of an investment.

So, consumers face a double challenge,

- firstly, in making an accurate and meaningful assessment of their willingness to accept risk as they perceive it, and
- secondly, in expressing this assessment in such a way that both what they already have in place, and the alternatives now on offer to them, can be evaluated in terms of their risk tolerance.

The ProQuest Personal Financial Profiling system assists consumers and their advisers in meeting this challenge. Developed in conjunction with the University of New South Wales' Applied Psychology Unit, it is the first Australian system to meet internationally accepted scientific standards.

In the questionnaire, you are asked about your attitudes, values and experiences. Your answers are scored against the system's database and used to produce a detailed report. The questionnaire takes about 15 minutes to complete.

By using the ProQuest system, you can obtain an accurate assessment of your risk tolerance in terms that are meaningful to you and your advisers. Your Risk Profile report will guide you and your advisers in your financial decision making. In particular, the report provides the basis for your instructions to your advisers on the level of risk you are willing to accept.

Please complete the registration details below and then proceed with the questionnaire.

Date Completed ____________________________

First Name ____________________________

Middle Initial _____

Last Name _____________________________________

Email Address (if any) _____________________________________

ProQuest respects your privacy and complies with the National Privacy Principles under Commonwealth legislation. ProQuest's full Privacy Statement can be found at: http://www.risk-profiling.com/privacypolicy.htm

Why are 25 questions needed?

A person's answer to a specific question may be influenced by a particular experience they have had, or their mood at the time. Or they may have misinterpreted the question. Or they may simply have made a mistake.

Statistical studies are used to determine the number of questions needed to provide a scientifically acceptable level of accuracy in an assessment. The accuracy of a questionnaire is a function, in part, of the square of the number of questions. Because of the nature of risk tolerance more than just a few questions are needed. Twenty would be a minimum.

Statistical studies of this questionnaire show that its accuracy exceeds internationally accepted standards.

What if the situation described in a question has never happened to me, or will never happen to me?

There are a number of questions that ask you to assume or imagine you are in a certain situation. These questions are designed to gain a picture of what you would do in such circumstances, regardless of whether you have ever been in them or are ever likely to be in them. Please answer as best you can on the available information

What if a question asks about a situation where, in real life, I would have (or would seek) more information than is given in the question?

Some questions require you to make a decision based on limited information. While, in real life, you may wish to obtain more information before making your final decision, these questions are designed to gain an idea of what you would do given the limited information. Please answer as best you can on the available information.

What if none of the choices in a multiple-choice question is my preferred answer?

Some questions give you a limited choice of responses and may not include what would be your preferred answer. These are designed to obtain a picture of what you would do given the choices available. Please answer as best you can on the available choices.

What makes a "good" questionnaire?

A good questionnaire will certainly be (relatively) easy to understand and answer. It must also have been developed on sound scientific principles in order to ensure the validity and reliability of its results. The starting point is a pool of potential questions. The trialing process these must go through will identify which questions work (statistically) and which do not. The questions that are effective in a questionnaire are not necessarily those most suitable for an interview.

The Risk Profile report produced from a completed questionnaire provides details of the development of the ProQuest questionnaire.

Do the questionnaire and report replace discussion between client and adviser?

Not at all. They act as catalysts to, and provide an objective starting point for, a more informed, more focussed discussion. Advisers experienced in using the ProQuest system report that the improved communication leads to clearer instructions from clients and greater understanding, by both client and adviser, of clients' attitudes to risk.

Risk Tolerance Questionnaire

Please answer all the questions by circling one of the options. Choose the option that best indicates how you feel about each question. If none of the options is exactly right for you, choose the option that is closest.

1. Compared to others, how do you rate your willingness to take financial risks?

1 Extremely low risk taker.
2 Very low risk taker.
3 Low risk taker.
4 Average risk taker.
5 High risk taker.
6 Very high ris k taker.
7 Extremely high risk taker.

2. How easily do you adapt when things go wrong financially?

1 Very uneasily.
2 Somewhat uneasily.
3 Somewhat easily.
4 Very easily.

3. When you think of the word "risk" in a financial context, which of the following words come to mind first?

1 Danger
2 Uncertainty
3 Opportunity
4 Thrill

4. Have you ever invested a large sum in a risky investment mainly for the 'thrill' of seeing whether it went up or down in value?

1 No.
2 Yes, very rarely.
3 Yes, somewhat rarely.
4 Yes, somewhat frequently.
5 Yes, very frequently.

5. If you had to choose between more job security with a small pay rise, and less job security with a big pay rise, which would you pick?

1 Definitely more job security with a small pay rise.
2 Probably more job security with a small pay rise.
3 Not sure.
4 Probably less job security with a big pay rise.
5 Definitely less job security with a big pay rise.

6. When faced with a major financial decision are you more concerned about the possible losses or the possible gains?

1 Always the possible losses.
2 Usually the possible losses.
3 Usually the possible gains.
4 Always the possible gains.

7. **How do you usually feel about your major financial decisions after you make them?**

   1 Very pessimistic.
   2 Somewhat pessimistic.
   3 Somewhat optimistic.
   4 Very optimis tic.

8. **Imagine you were in a job where you could choose to be paid salary, commission or a mix of both. Which would you pick?**

   1 All salary.
   2 Mainly salary.
   3 Equal mix of salary and commission.
   4 Mainly commission
   5 All commission.

9. **What degree of risk have you taken with your financial decisions in the pas t?**

   1 Very small.
   2 Small.
   3 Medium.
   4 Large.
   5 Very large.

10. **What degree of risk are you currently prepared to take with your financial decisions?**

    1 Very small.
    2 Small.
    3 Medium.
    4 Large.
    5 Very large.

11. **Have you eve r borrowed money to make an investment (other than for your home)?**

    1 No.
    2 Yes.

12. **How much confidence do you have in your ability to make good financial decisions?**

    1 None.
    2 A little.
    3 A reasonable amount.
    4 A great deal.
    5 Complete.

13. **Suppose that 5 years ago you bought shares in a highly regarded company. That same year the company experienced a severe decline in sales due to poor management. The price of the shares dropped drastically and you sold at a substantial loss.**

    The company has been restructured under new management and most experts now expect its shares to produce better than average returns. Given your bad past experience with this company would you buy shares now?

    1 Definitely not.
    2 Probably not.
    3 Not sure
    4 Probably.
    5 Definitely.

14. **Investments can go up and down in value and experts often say you should be prepared to weather a downturn. By how much could the total value of <u>all your investments</u> go down before you would begin to feel uncomfortable?**

    1 Any fall in value would make me feel uncomfortable.
    2 10%.
    3 20%.
    4 33%.
    5 50%.
    6 More than 50%.

15. **Assume that a long-lost relative dies and leaves you a house which is in a poor condition but it is located in a suburb that's becoming popular.**
    As is, the house would probably sell for $150,000, but if you were to spend about $50,000 on renovations, the selling price would be around $300,000.
    However, there's some talk of constructing a major highway next to the house, and this would lower its value considerably.

    Which of the following options would you take?

    1 Sell it as is.
    2 Keep it as is, but rent it out
    3 Take out a $50,000 mortgage and do the renovations.

16. **Most investment portfolios have a spread of investments - some of the investments may have high expected returns but with high risk, some may have medium expected returns and medium risk, and some may be low risk/low return. (For example, shares and property would be high risk/high return whereas cash and term deposits would be low risk/low return.)**

    Which spread of investments do you find most appealing? Would you prefer all low risk/low return, all high risk/high return, or somewhere in between?

<u>Spread of Investments in Portfolio</u>

Portfolio	High Risk/Return	Medium Risk/Return	Low Risk/Return
1	0%	0%	100%
2	0%	30%	70%
3	10%	40%	50%
4	30%	40%	30%
5	50%	40%	10%
6	70%	30%	0%
7	100%	0%	0%

17. **You are considering placing one-quarter of your investment funds into a single investment. This investment is expected to earn about twice the term deposit rate. However, unlike a term deposit, this investment is not protected against loss of the money invested.**
    How low would the chance of a loss have to be for you to make the investment?

    1 Zero, i.e., no chance of any loss.
    2 Very low chance of loss.
    3 Moderately low chance of loss.
    4 50% chance of loss.

18. With some types of investment, such as cash and term deposits, the money value of the investment is fixed. However inflation will cause the purchasing power of this money value to decrease.

With other types of investment, such as shares and property, the money value is not fixed. It will vary. In the short term it may even fall below the purchase price. However, over the long term, the money value of shares and property should certainly increase by more than the rate of inflation.

With this in mind, which is more important to you, that the money value of your investments does not fall or that it retains its purchasing power?

1 Much more important that the money value does not fall.
2 Somewhat more important that the money value does not fall.
3 Somewhat more important that the money value retains its purchasing power.
4 Much more important the money value retains its purchasing power.

19. In recent years, how have your personal investments changed?

1 Always toward lower risk.
2 Mostly toward lower risk.
3 No changes or changes with no clear direction.
4 Mostly toward higher risk.
5 Always toward higher risk.

20. When making an investment, return and risk usually go hand-in-hand. Investments which produce above average returns are usually of above average risk.
With this in mind, how much of the funds you have available to invest would you be willing to place in investments where both returns and risks are expected to be above average?

1 None.
2 10%.
3 20%.
4 30%.
5 40%.
6 50%.
7 60%.
8 70%.
9 80%.
10 90%.
11 100%.

21. Think of the average rate of return you would expect to earn on an investment portfolio over the next ten years. How does this compare with what you think you would earn if you invested the money in term deposits?

1 About the same rate as from term deposits.
2 About one and a half times the rate from term deposits.
3 About twice the rate from term deposits.
4 About two and a half times the rate from term deposits.
5 About three times the rate from term deposits.
6 More than three times the rate from term deposits.

22. **People often arrange their financial affairs so as to qualify for a government benefit or to obtain a tax advantage. However a change in legislation can leave them worse off than if they'd done nothing. With this in mind, would you take a risk in arranging your affairs to qualify for a government benefit or obtain a tax advantage?**

1 I would not take a risk if there was any chance I could finish up worse off.
2 I would take a risk if there was only a small chance I could finish up worse off.
3 I would take a risk as long as there was more than a 50% chance that I would finish up better off.

23. **Imagine that you are borrowing a large sum of money at some time in the future. It's not clear which way interest rates are going to move - they might go up, they might go down, no one seems to know. You can have a variable interest rate that will rise and fall as the market rate changes, a fixed interest rate which is 1% more than the then variable rate but which won't change as the market rate changes, or a mixture of both.**
How would you prefer your loan to be made up?

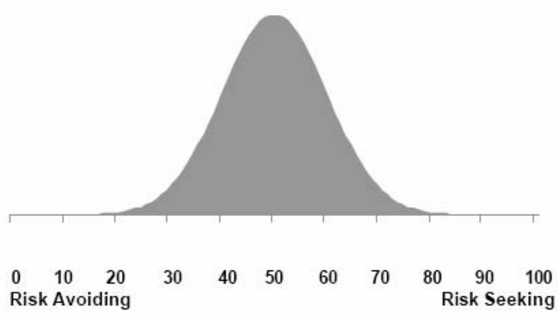
1 100% variable.
2 75% variable, 25% fixed.
3 50% variable, 50% fixed.
4 25% variable, 75% fixed.
5 100% fixed.

24. **Insurance can cover a wide variety of life's major risks – theft, fire, accident, illness, death, etc. How much cover do you have?**

1 Very little.
2 Some.
3 Considerable.
4 Complete.

25. **This questionnaire is scored on a scale of 0 to 100. In practice, however, the scores range from around 20 to around 80, with the average being 50.**

When the scores are graphed they follow the familiar bell-shaped curve of the Normal distribution (see below). About two-thirds of all scores are within 10 points of the average.



What do you think your score will be?_____

Demographic Questionnaire

Finally, a few questions about yourself to help us better understand the pattern of Risk Tolerance in our community.

1. **I am**

   1 Male. 2 Female.

2. **My year of birth is 19___**

3. **My residential postcode is _______**

4. **The highest education level I attained, or the closest equivalent, is**

   1 Did not complete high school.
   2 Completed high school.
   3 Trade or diploma qualification.
   4 University degree or higher qualification.

5. **Having in mind income from all sources - work, investment, family and government - into which income bracket does your personal before-tax income fall?**

   1 Under $30,000.
   2 $30,000 - $50,000.
   3 $50,000 - $100,000.
   4 $100,000 - $200,000.
   5 Over $200,000.

6.(a) **Are you married (or in a de facto relationship)?**

   1 Yes.
   2 No.

(b) **If "Yes", into which income bracket does your combined before-tax income fall?**

   1 Under $30,000.
   2 $30,000 - $50,000.
   3 $50,000 - $100,000.
   4 $100,000 - $200,000.
   5 Over $200,000.

7. **How many people in your family, beside yourself, do you fully or partially support financially? _____**

8. **Think of your net assets as being what you own, including your family home and other personal-use assets, minus what you owe. Into which bracket does the value of your net assets fall? (If you are married or have a de facto partner, include your share of jointly owned assets.)**

5	Under $10,000.	10	$150,000 - $250,000.
6	$10,000 - $25,000.	11	$250,000 - $500,000.
7	$25,000 - $50,000.	12	$500,000 - $1,000,000.
8	$50,000 - $100,000.	13	$1,000,000 - $2,500,000.
9	$100,000 - $150,000.	14	Over $2,500,000.

You may wish to review your answers before returning the questionnaire to your advisers. In order to have your Risk Tolerance report prepared, you must answer all 25 questions in the Risk Questionnaire. Now is the best time to check for omissions and correct any mistakes.

Once your answers are recorded in the ProQuest system they cannot be changed. This is done to ensure the integrity of the data. If, later, you wish to change an answer, this can only be done by entering a completely new set of answers which includes the change.

Chapter 3: An Empirical Investigation of Personal Financial Risk Tolerance – Extended Analysis With a Large Database[13]

3.1. Introduction

The exploratory analysis in Chapter 2 found that the gender, age, income and wealth demographics were determinants of financial risk tolerance, although the relationships found were not as simple as implied by the demographic heuristics. However, education, marital status and dependents, which have been found to be significant in previous studies, were not found to be significant determinants of an individual's attitude towards risk in that study.

The purpose of the research in this chapter is to provide further evidence as to the behavior and 'determinants' of investor risk tolerance. In addition to an analysis of the relationship between risk tolerance and general demographics, special attention shall be given to issues surrounding age and marital status. To this end, a database has been compiled which consists of a psychometrically derived financial risk tolerance score (RTS) for over 20,000 surveyed individuals as well as each respondent's demographic characteristics. This data shall be analysed to provide further empirical insights into the nature of investor risk tolerance.

The remainder of this Chapter proceeds as follows. Section 3.2 details the risk tolerance database and sample used in this paper. Section 3.3 presents the results of econometric analysis into the determinants of risk tolerance as well as some observations as to the nature of risk tolerance among investors. Section 3.4 summarises our findings.

---

[13] Parts of this chapter are drawn from a paper published by the candidate: Hallahan, T., Faff, R. and MacKenzie, M. (2004). An Empirical Investigation of Personal Financial Risk Tolerance, *Financial Services Review*, 13, 57-78.

3.2. Sample Description

The FinaMetrica database used in this study consists of the RTS and associated demographics for individuals who have completed the test over the period May, 1999 to February 2002. The majority of these data are sourced from clients of personal financial planners who take this test as a first step in constructing a personalised financial plan. Access to the survey is online via the FinaMetrica website. A subset of the data (approximately 1900 observations) were respondents who completed the test in response to an invitation made to readers of Personal Investor magazine. The Personal Investor readers completed the test by visiting the magazine's website where they could then access an internet link to the FinaMetrica website.[14]

Following the approach discussed in Section 2.2, respondents who recorded their year of birth implying an age of less than 20 years or older than 80 years, and respondents who generated an RTS outside the range 20-95 were omitted from the analysis, as such responses were not considered plausible.[15] A total of 356 respondents were excluded on these criteria, leaving a sample of 20,415. Almost all respondents are Australian, with approximately only 0.5% giving an international home address.

A summary of the demographic information for the investors captured in this database is presented in Table 3.1. Unfortunately, not all of the respondents who completed the survey and received an assessment of their financial risk tolerance also completed all of the demographic questions. As such, the number of observations for each demographic will be less than the total size of the RTS database. The 'typical' respondent in the survey is a

[14] The Personal Investor data does not significantly differ from the main database.
[15] Application of the age filter resulted in the exclusion of 129 observations while the RTS boundary excluded a further 66 responses.

married university educated male who is 51 – 60 years old with an annual income of $50,000 - $100,000 and net assets of $150,000 - $500,000.

Table 3.1 Summary of the FinaMetrica Dataset by Demographics

	Number of Observations	% of Sample
Panel A: Gender		
Males	14444	70.75
Females	5971	29.25
Total Responses	20415	
Panel B: Age		
< 30 years old	2359	13.67
30-40 years old	3957	22.93
41-50 years old	4012	23.25
51-60 years old	4399	25.49
>60 years old	2528	14.65
Total Responses	17255	
Panel C: Education (highest qualification attained)		
Did not Complete High School	1369	8.00
High School	2878	16.81
Trade/Diploma	4292	25.07
University	8582	50.13
Total Responses	17121	
Panel D: Marital Status		
Married (incl. Defacto)	13217	77.66
Unmarried	3802	22.34
Total Responses	17019	
Panel E: Income		
< $30,000	3454	20.53
$30,000-$50,000	3989	23.71
$50,000-$100,000	5340	31.74
$100,000-$200,000	3018	17.94
>$200,000	1025	6.09
Total Responses	16826	
Panel F: Net Assets		
< $50,000	2118	12.87
$50,000-$150,000	2349	14.27
$150,000-$500,000	5884	35.75
$500,000-$1,000,000	3481	21.15
>$1,000,000	2629	15.97
Total Responses	16461	

More specifically, Panel A of Table 3.1 reveals that males (70.75%) represent a higher proportion of the database compared to females (29.25%). Panel B shows that a relatively small number of investors aged less than 30 years are represented in the database while the majority (25.49%) are aged 51- 60. This is to be expected given that people are more concerned with their ability to provide for themselves the closer retirement looms. As such, the likelihood of an individual seeking advice from a financial planner and undertaking the FinaMetrica survey increases with age which is reflected in these demographics.

The highest educational qualification attained for the respondents is summarised in Panel C of Table 3.1 and just on half of the individuals who answered this demographic question had completed university. This result may be biased as individuals who did not complete some form of tertiary education may not be inclined to answer. One interesting issue this demographic information raises is whether more educated individuals have more money and so they are more likely to need to services of a financial planner and hence undertake the FinaMetrica survey. This is an empirical issue, which will be considered later in this chapter.

The majority of the survey respondents are married (77.66%), and when combined with the earlier evidence as to the gender composition of the database, this demographic information tends to reinforce the notion that males are the primary source of financial decision making in households. Finally, Panel E and F summarise the income and wealth composition of the database, respectively. Almost half of the respondents answering this question earn $50,000 or less (44%) while 56% own assets of between $150,000 and $1,000,000. Taken in conjunction with the age information discussed earlier, this tends to suggest that the typical survey respondent is nearing or at retirement and is asset rich and income poor.

3.3. Empirical Analysis

Analysis of the dataset has two facets: investigating the relationship between subjective and objective estimates of risk tolerance (Section 3.3.1), and exploring the relationship between demographic variables and risk tolerance scores (Section 3.3.2).

3.3.1. Self-Assessed Risk Tolerance

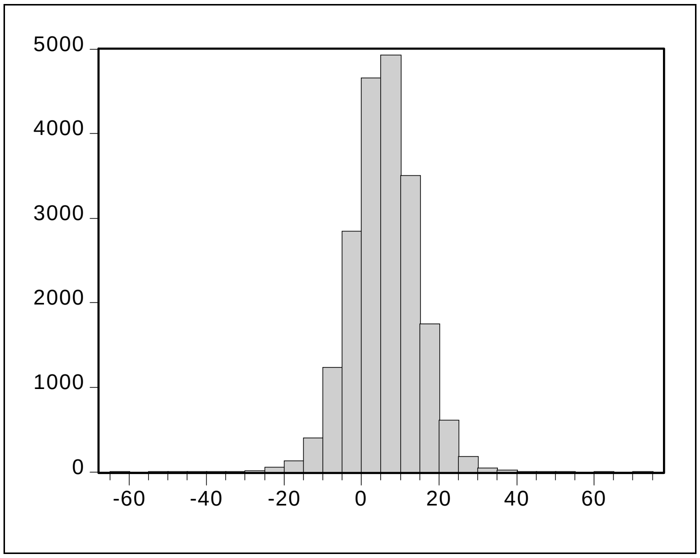
The FinaMetrica survey contains a question in which respondents are asked to estimate their RTS *ex ante*.[16] It is interesting to consider the relationship between their self-assessed risk tolerance (SRTS) and that estimated by the FinaMetrica survey. As a first step in the analysis, it was found that the average difference between the RTS and SRTS is 5.33 ($\sigma = 8.49$). This suggests that individuals typically underestimate their risk tolerance score by approximately 5 points. In unreported results the indication is that the younger, more educated and higher income respondents have a greater tendency to underestimate their financial risk tolerance.

Recall that the RTS is measured on a scale from 0-100 and so it would appear that most peoples' assessment of their capacity to bear risk accords to their revealed preferences as indicated by their answers to the survey. This is not true of all respondents however, as the maximum difference was 74 points and the minimum difference was –63 points.[17] A histogram of the data is presented in Figure 3.1. The analysis revealed that 803 individuals were correct in their estimation of their own RTS, 4691 individuals overestimated and 14,921 underestimated their RTS. Thus, for some individuals, their answers to the survey suggested a risk tolerance far different from their own perception of their ability to absorb risk and the majority tended to underestimate their risk tolerance to varying degrees.

[16] The actual question reads: "This questionnaire is scored on a scale of 0 to 100. In practice, however, the scores range from around 20 to around 80, with the average being 50. When the scores are graphed they follow the familiar bell-shaped curve of the Normal Distribution (diagram provided). About two-thirds of all scores are within 10 points of the average. What do you think your score will be?"

[17] These extreme values are not the norm and 99% of the differences fell in the range of ±25 points. FinaMetrica consider approximately ±20 points to be within the bounds of possibility.

Figure 3.1 Histogram of the Difference Between Actual and Self-Assessed Risk Tolerance Score



Further insights to this relationship may be gained by estimating a regression equation between SRTS and the FinaMetrica RTS. The estimated regression output may be summarised as follows:

$$\text{SRTS} = 4.12 + 0.838\ \text{RTS}$$

$$\text{t-statistic:} \quad (15.19) \quad (185.67)$$

$$R^2 = 0.628, \text{ F-stat (p-value)} = 0.000$$

The estimated coefficients verify the significant positive association between people's own perception of their risk tolerance and the RTS. On average, a respondent's self-assessed RTS is approximately 4.12 points plus 83.8% of their actual RTS.

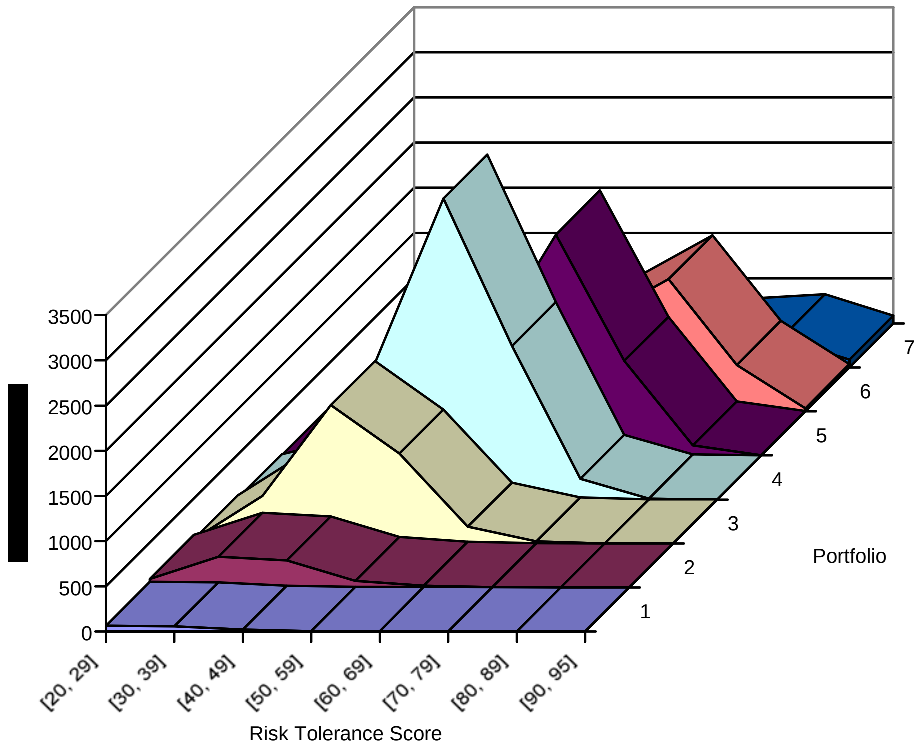
Another way in which the consistency between individuals expressed and revealed risk preferences may be established is to cross reference their RTS with their answer to a question from the FinaMetrica survey in which respondents were asked to choose the most appealing portfolio from a selection each of which is composed of a different mix of high, medium and low risk/return assets: [18]

Portfolio	Risk/Return		
	High	Medium	Low
1	0%	0%	100%
2	0%	30%	70%
3	10%	40%	50%
4	30%	40%	30%
5	50%	40%	10%
6	70%	30%	0%
7	100%	0%	0%

Figure 3.2 presents information as to the number of respondents (Z-axis) selecting each of the seven portfolios (Y-axis) grouped by RTS (X-axis). Portfolio 4, which contains the most even mix of the three asset classes, is the most popular choice among investors (6986 or 34% of the observations). The RTS of individuals selecting this portfolio ranged from 20 to 90, however the majority (3327 observations) possessed a RTS of between 50 – 59. The second most popular portfolio was number five which was a more aggressive portfolio with a relatively higher weighting of high risk/high return assets (4981 observations). Portfolios three and six were preferred by a similar number of investors (3309 and 3284, respectively) while relatively few investors chose portfolios one, two or seven (160, 834 and 807, respectively). Thus, the responses of investors are logically consistent as the 'average' investor (in terms of RTS) most commonly selected the 'average' portfolio (in terms of the most even mix of assets).

[18] The actual question reads: "Most Investment portfolios have a spread of investments - some of the investments may have a high expected returns but with high risk, some may have medium expected returns and medium risk, and some may be low risk/low return (For example, shares and property would be high risk/high return, whereas cash and term deposits would be low risk/low return). Which spread of investments do you find the most appealing? Would you prefer all low risk/low return, all high risk/high return or somewhere in between?" (table presented)

Figure 3.2 Investor Risk Tolerance and Portfolio Composition

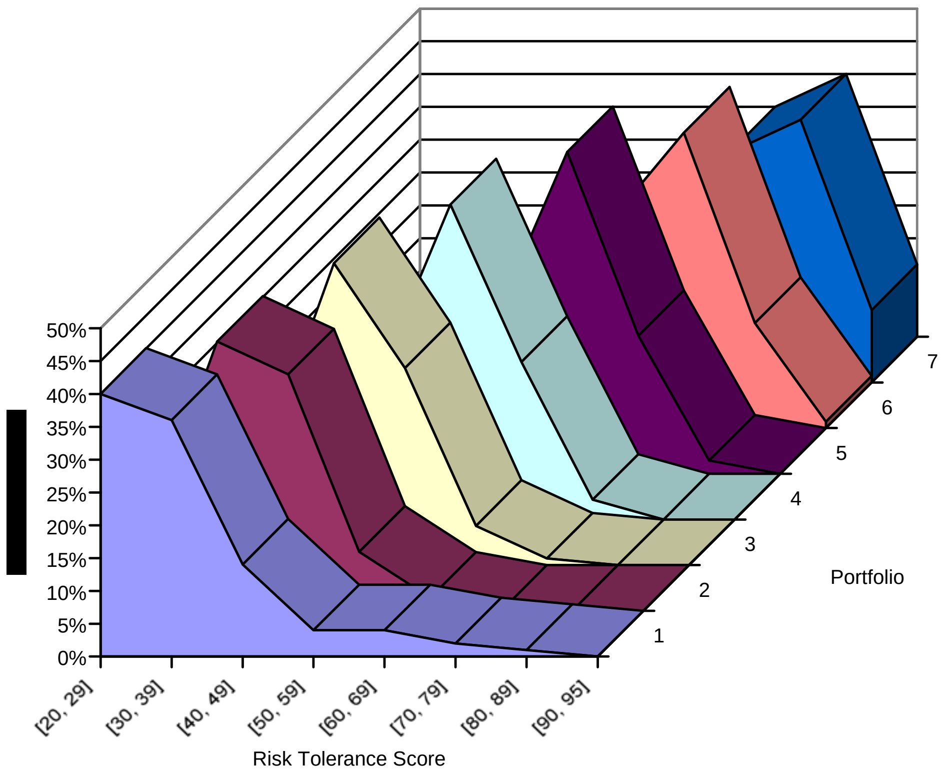


This figure presents information as to the number of respondents (Y-axis) selecting one of seven portfolios (Z-axis) grouped by RTS (X-axis). Each portfolio contains a different mix of low/medium/high risk assets with successively higher numbered portfolios weighted more toward the high risk/return asset.

Given the increasing risk associated with each successively higher numbered portfolio, logic suggests that the average RTS of investors preferring each portfolio should also increase. This would be consistent with the peak of the surface for each portfolio occurring at a higher RTS. It is not easy to distinguish these peaks from Figure 3.2 due to the different number of observations in each portfolio. As such, Figure 3.3 shows investors preferences for each portfolio grouped by RTS where the Y-axis is expressed as a percentage of the total number of investors choosing each portfolio. Portfolio 1 contains the low risk/return spread of investments and it was most frequently selected (40%) by investors with an RTS of between

20 – 29. For higher portfolios, which exhibit a higher level of risk/return, the most frequently observed RTS of individuals selecting that portfolio successively increases which is consistent with our expectations. This highest risk/return portfolio (portfolio 7) was most commonly selected by individuals with a RTS of 80 – 90 (40%). These results suggest that people tend to choose a portfolio which is consistent with their inherent propensity to bear risk.

Figure 3.3 Investor Risk Tolerance and Portfolio Composition (Percentage)



This figure presents information on the percentage of the total number of investors (Y-axis) selecting one of seven portfolios (Z-axis) grouped by RTS (X-axis). Each portfolio contains a different mix of low/medium/high risk assets with successively higher numbered portfolios weighted more toward the high risk/return asset.

In general, the results serve to confirm the rationality of individual's choices. Investors responses to individual questions, which represent their expressed preferences, are broadly consistent with their overall level of risk tolerance, ie. their revealed preference.[19]

[19] It is acknowledged there is an element of endogeneity to this analysis as the answers to these two questions are used to generate the FinaMetrica estimate of RTS but it is considered to be an interesting outcome nonetheless.

3.3.2. The Role of Demographic Factors

The FinaMetrica database contains information on a number of different demographic factors for each respondent, namely, age, number of dependents, gender, marital status, education, personal income, combined family income and net assets. As discussed in Section 3.1, past research involving these variables has provided conflicting results. Accordingly, hierarchical regression was employed to assess which of the variables make a significant contribution to the prediction of risk tolerance. The hierarchical regression was structured with the interval-level variables for the demographic characteristics of age and the number of dependents constituting the base-case regression. In light of the results of Riley and Chow (1992) and Bajtelsmit and VanDerhai (1997, a test for the presence of nonlinearities in the relationship between age and risk tolerance was included in the form of a quadratic age term. The remaining demographic characteristics, that is, gender, marital status, education, income, combined income and net assets, which enter the FinaMetrica database as ordinal-level variables, were dummy coded and entered sequentially as separate sets of predictors, judged in order of importance having reference to past research.

The results of estimating this model are presented in Table 3.2. The incremental change in the reported R^2 values indicates the contribution toward prediction of each of the ordinal-level independent variables. Consistent with the bulk of prior research, the greatest change in the R^2 values above the base-case is associated with the introduction of the first variable, gender, as an explanatory variable. Interestingly, the subsequent addition of marital status fails to increase the explanatory power of the regression. The increments to the R^2 values generated by the sequential introduction of the remaining variables show a pattern of monotonic increase, confirming that these variables make a significant contribution to the prediction of risk tolerance scores.

Table 3.2 Heirachical Regression of Financial Risk Tolerance on Demographic Variables

$RTS_i = \alpha_0 + \alpha_1 AGE_i + \alpha_2 AGE_i^2 + \alpha_3 NDEP_i + \varepsilon_i$	$R^2 = 0.114$
$RTS_i = \alpha_0 + \alpha_1 AGE_i + \alpha_2 AGE_i^2 + \alpha_3 NDEP_i + \alpha_4 D_{i,FEM} + \varepsilon_i$	$R^2 = 0.187$ F-stat = 946.53 P-value =0.000
$RTS_i = \alpha_0 + \alpha_1 AGE_i + \alpha_2 AGE_i^2 + \alpha_3 NDEP_i + \alpha_4 D_{i,FEM} + \alpha_5 D_{i,MARRIED} + \varepsilon_i$	$R^2 = 0.187$ F-stat = 757.56 P-value = 0.210
$RTS_i = \alpha_0 + \alpha_1 AGE_i + \alpha_2 AGE_i^2 + \alpha_3 NDEP_i + \alpha_4 D_{i,FEM} + \alpha_5 D_{i,MARRIED} + \sum_{g=EDU_2}^{EDU_4} \alpha_g D_{i,g} + \varepsilon_i$	$R^2 = 0.208$ F-stat = 538.41 P-value = 0.000
$RTS_i = \alpha_0 + \alpha_1 AGE_i + \alpha_2 AGE_i^2 + \alpha_3 NDEP_i + \alpha_4 D_{i,FEM} + \alpha_5 D_{i,MARRIED} + \sum_{g=EDU_2}^{EDU_4} \alpha_g D_{i,g} + \sum_{h=INC_2}^{INC_5} \alpha_h D_{i,h} + \varepsilon_i$	$R^2 = 0.229$ F-stat = 405.94 P-value = 0.000
$RTS_i = \alpha_0 + \alpha_1 AGE_i + \alpha_2 AGE_i^2 + \alpha_3 NDEP_i + \alpha_4 D_{i,FEM} + \alpha_5 D_{i,MARRIED} + \sum_{g=EDU_2}^{EDU_4} \alpha_g D_{i,g} + \sum_{h=INC_2}^{INC_5} \alpha_h D_{i,h} + \sum_{j=CINC_2}^{CINC_5} \alpha_j D_{i,j} + \varepsilon_i$	$R^2 = 0.233$ F-stat = 312.15 P-value = 0.000
$RTS_i = \alpha_0 + \alpha_1 AGE_i + \alpha_2 AGE_i^2 + \alpha_3 NDEP_i + \alpha_4 D_{i,FEM} + \alpha_5 D_{i,MARRIED} + \sum_{g=EDU_2}^{EDU_4} \alpha_g D_{i,g} + \sum_{h=INC_2}^{INC_5} \alpha_h D_{i,h} + \sum_{j=CINC_2}^{CINC_5} \alpha_j D_{i,j} + \sum_{k=NASS_2}^{NASS_5} \alpha_k D_{i,k} + \varepsilon_i$	$R^2 = 0.239$ F-stat = 257.53 P-value = 0.000

The final hierarchical regression model contains the full set of predictors and provides a quantification of the relationship between each of the demographic characteristics and RTS according to the following specification:

$$RTS_i = \alpha_0 + \alpha_1 D_{i,FEM} + \alpha_2 AGE_i + \alpha_3 AGE_i^2 + \alpha_4 NDEP_i + \alpha_5 D_{i,MARRIED} + \sum_{g=EDU_2}^{EDU_4} \alpha_g D_{i,g} + \sum_{h=INC_2}^{INC_5} \alpha_h D_{i,h} + \sum_{j=CINC_2}^{CINC_5} \alpha_j D_{i,j} + \sum_{k=NASS_2}^{NASS_5} \alpha_k D_{i,k} + \varepsilon_i \quad (3.1)$$

where RTS_i is the financial risk tolerance score for individual *i* provided by FinaMetrica based on the answers to their Risk Tolerance Questionnaire and takes a possible value between 0 and 100 and:

- D_{FEM} is a dummy variable that signifies a respondent is female;
- AGE is the age of the respondent;
- AGE^2 is a quadratic age term
- NDEP is the number of people in the family whom are financially dependent on the respondent;
- $D_{MARRIED}$ is a dummy variable that takes a value of unity if the respondent is married (legally or defacto);
- D_{EDU} captures the completed level of education of the respondent and includes did not complete high school (D_{EDU1}), completed high school (D_{EDU2}), trade/diploma (D_{EDU3}), or university (D_{EDU4}) level of education;
- D_{INC} shows the respondent's income as, < \$30,000 (D_{INC1}), \$30,000 - \$50,000 (D_{INC2}), \$50,000-\$100,000 (D_{INC3}), \$100,000-\$200,000 (D_{INC4}) or > \$200,000 (D_{INC5});
- D_{CINC} indicates if the respondent's combined family income is, <\$30,000 (D_{CINC1}), \$30,000 - \$50,000 (D_{CINC2}), \$50,000-\$100,000 (D_{CINC3}), \$100,000-\$200,000 (D_{CINC4}), or > \$200,000 (D_{CINC5});
- D_{NASS} takes a value of unity if the respondent's net assets are <\$50,000 (D_{NASS1}), \$50,000 - \$150,000 (D_{NASS2}), \$150,000-\$500,000 (D_{NASS3}), \$500,000-\$1,000,000 (D_{NASS4}) or > \$1,000,000 (D_{NASS5}).

The results of estimating this model are presented in Table 3.3.

Table 3.3 Regression of Financial Risk Tolerance on Demographic Variables

Variable	Coefficient	Std. Error	t-statistic	p-value.
α_0	62.3874	1.1413	54.66	0.000
D_{FEM}	-6.2031	0.2032	-30.53	0.000
AGE	0.0344	0.0528	0.65	0.515
AGE^2	-0.0037	0.0006	-6.68	0.000
NDEP	-0.1921	0.0734	-2.62	0.009
$D_{MARRIED}$	-2.2212	0.3972	-5.59	0.000
D_{EDU2}	0.6674	0.3750	1.78	0.075
D_{EDU3}	2.0019	0.3561	5.62	0.000
D_{EDU4}	3.2289	0.3479	9.28	0.000
D_{INC2}	0.9968	0.2766	3.60	0.000
D_{INC3}	2.9354	0.2911	10.08	0.000
D_{INC4}	3.5479	0.3405	10.42	0.000
D_{INC5}	2.7522	0.5851	4.70	0.000
D_{CINC2}	0.7248	0.4198	1.73	0.084
D_{CINC3}	1.7483	0.3915	4.47	0.000
D_{CINC4}	2.8219	0.4220	6.69	0.000
D_{CINC5}	3.0323	0.5578	5.44	0.000
D_{NASS2}	1.6275	0.3556	4.58	0.000
D_{NASS3}	1.4132	0.3437	4.11	0.000
D_{NASS4}	3.1242	0.3867	8.08	0.000
D_{NASS5}	3.9484	0.4289	9.21	0.000

Adjusted R-squared = 0.2384 F-stat = 257.53 (P-value = 0.000)

Wald Tests of Coefficient Equality:	($D_{INC2} = D_{INC3} = D_{INC4} = D_{INC5}$)	P-value = 0.000
	($D_{INC4} = D_{INC5}$)	P-value = 0.130
	($D_{CINC2} = D_{CINC3} = D_{CINC4} = D_{CINC5}$)	P-value = 0.000
	($D_{NASS2} = D_{NASS3} = D_{NASS4} = D_{NASS5}$)	P-value = 0.000
	($D_{NASS4} = D_{NASS5}$)	P-value = 0.006

This table presents a summary of the estimated regression output for the equation:

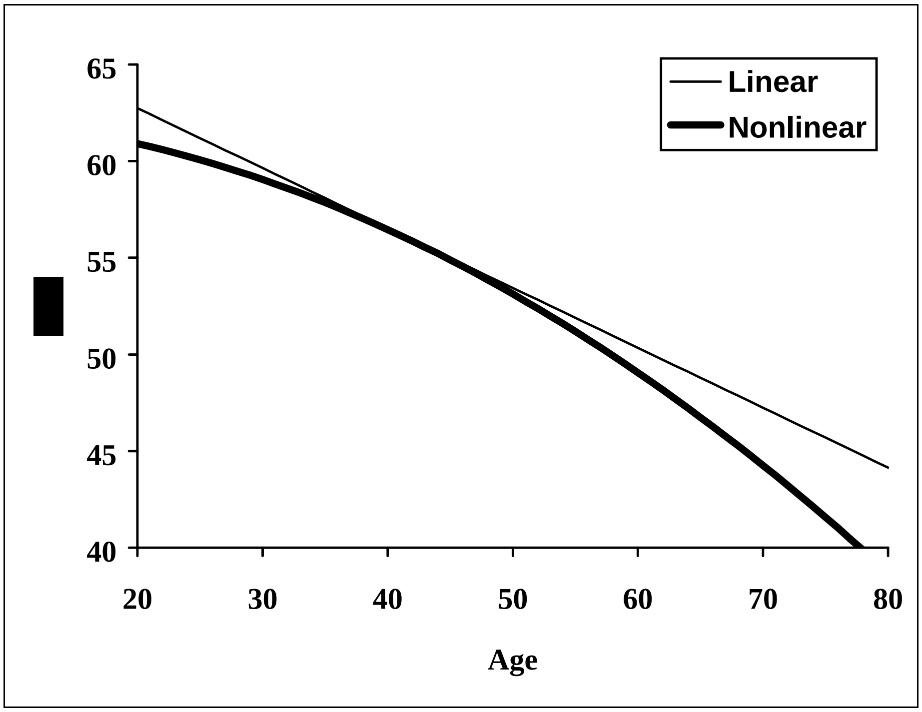
$$RTS_i = \alpha_0 + \alpha_1 D_{i,FEM} + \alpha_2 AGE_i + \alpha_3 AGE_i^2 + \alpha_4 NDEP_i + \alpha_5 D_{i,MARRIED} + \sum_{g=EDU_2}^{EDU_4} \alpha_g D_{i,g} + \sum_{h=INC_2}^{INC_5} \alpha_h D_{i,h} + \sum_{j=CINC_2}^{CINC_5} \alpha_j D_{i,j} + \sum_{k=NASS_2}^{NASS_5} \alpha_k D_{i,k} + \varepsilon_i$$

where RTS_i is the FinaMetrica RTS for individual i, Age is the age expressed in years, NDEP is the number of financial dependents, D are dummy variables for gender (FEM), marital status (MARRIED), education (EDU), income (INC) and combined income (CINC), and α are the coefficients to be estimated.

The constant term in this model of 62.39 captures the omitted case which is an unqualified unmarried male with no dependents and having a personal and family income of less than $30,000 and net assets of less than $50,000. The RTS for individuals who differ from the base case can be assessed by considering the significance and sign of the estimated coefficients in the model. Gender is a significant determinant of risk tolerance and a female will exhibit an RTS of 6.20 points less compared to a demographically equivalent male. Similarly, age (squared) and marital status are found to be significant determinants of the RTS. While marriage simply decreases the RTS by two points, the relationship between age and RTS is revealed as more complex: the regression output shows that the age variable is nonsignificant, while the nonlinear age term is highly significant. This provides clear evidence as to the presence of nonlinear effects in the relationship between age and RTS: the negative sign of the coefficient on the quadratic age variable term (α_3) indicates that risk tolerance declines at an increasing rate as age increases.

As the constant term in the model is based on an age of zero, the RTS for a representative individual aged, for example, 20 years becomes 60.91 (62.39+400*-0.0037). Figure 3.4 provides a comparative plot of the relationship between age and RTS in the linear (as given by an unreported estimation of equation 3.1 minus the quadratic term) and nonlinear (as given by equation 3.1 above) case. The nonlinear nature of this relationship can clearly be seen and reveals the extent to which the change in RTS for a change in age increases the older the individual concerned. The relationship between RTS and the other demographic variables included in this regression equation are entirely consistent with those discussed in Section 3.2 and so a more detailed discussion of these non-age variables is excluded for the sake of brevity.

Figure 3.4 Forecast RTS using a Linear and Nonlinear Age Variable



This diagram forecasts the risk tolerance score for different aged investors. The nonlinear forecast represents the base case individual of Table 3.3 plus an adjustment for age as given by the quadratic age coefficient in that table. The linear forecast represents the base case individual of Table 3.3 where the model is estimated excluding the quadratic age coefficient.

The series of dummy variables capturing the level of income of an individual (D_{INC}) were all individually significant and positive as were the net asset (D_{NASS}) dummy variables. The estimated results indicate that the RTS of an individual generally increases as income and assets increases. A Wald test of coefficient equality rejects the null hypothesis of coefficient equality for the income, combined income and net asset dummy variables, respectively. This positive relationship between income, assets and risk tolerance does not appear to be uniform. Specifically, higher levels of income are found to be associated with successively higher RTS except for the top income bracket. Although the increment to the RTS over the base case is still positive (D_{INC5} = 2.75), it is less than that found for the income bracket preceding it (D_{INC4} = 3.55). A Wald test of coefficient equality however, between D_{INC4} and D_{INC5} generates a *p-value* of 0.130 which suggests this difference is not statistically significant.

Not all of the demographic characteristics tested in equation (1) were found to be significant. In terms of the level of education of an individual, at least a trade/diploma level of education was required before a significant increase (at the 5% level) in RTS was observed. Further, the number of dependents was found to be significantly associated with RTS for the sample group, although the impact on RTS is small in magnitude.

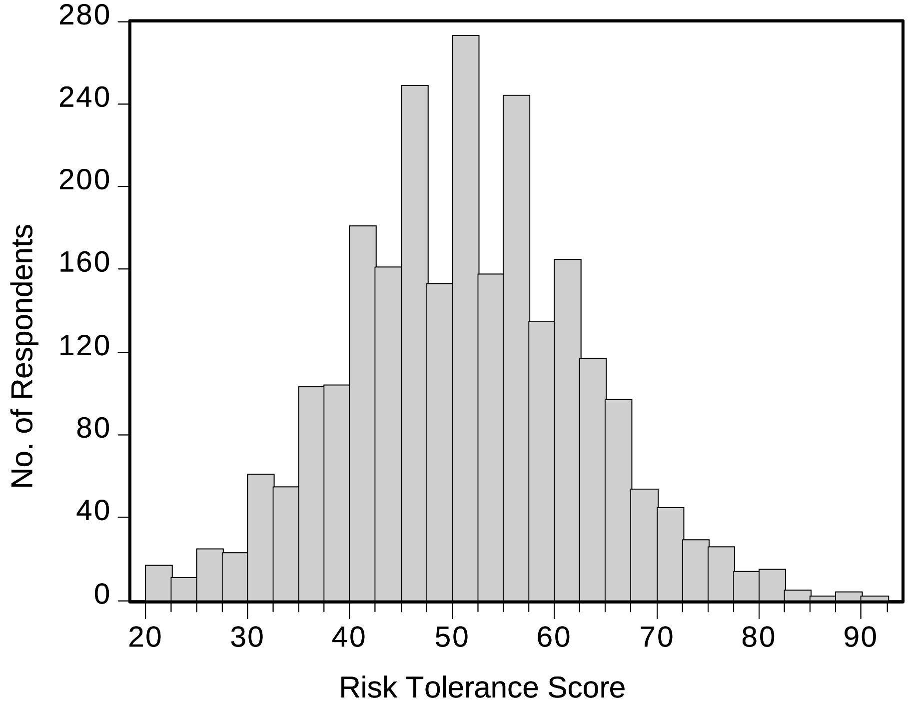
Overall, these results suggest that gender, age, number of dependents, marital status, tertiary education, income and wealth are all related to risk tolerance. The results for gender, education and income are consistent with the earlier literature. However, the positive relationship for wealth and RTS contrasts with the results of Bernheim et al (2001) who found no relationship between risk tolerance and wealth.

3.3.3. Age and Risk Tolerance

The negative relationship between age-squared and RTS, discussed in the previous section, is a particularly interesting result: while consistent with the findings from the smaller sample study presented in Chapter 2, it nevertheless conflicts with much of the current literature which has found that a positive or no relationship between age and risk tolerance exists (see Wang and Hanna 1997; Grable and Joo 1997; Grable and Lytton 1998, Hanna et al., 1998; Grable 2000, Hariharan et al., 2000; and Gollier and Zeckhauser, 2002), although the presence of non-linearity is consistent in that regard with the findings of Riley and Chow (1992) and Bajtelsmit and VanDerhai (1997).

Further insights on the relationship between age and RTS may be gained by focusing the analysis on those individuals who recorded their age as over 60. Table 3.4, Panel A reveals this group of retired and semi-retired individuals generated the lowest RTS of 51.02 and exhibited the smallest variation of scores (compared to unreported results for similar analysis of the full dataset). This is not to suggest that this age group of investors do not exhibit a diversity of risk profiles. A histogram of the RTS for this subgroup of our data is presented in Figure 3.5 and shows that 60+ investors are a very heterogenous group with a wide distribution of RTS ranging from extremely conservative to highly risk tolerant.

Figure 3. 5 Histogram of Risk Tolerance Scores For Individuals Over 60



This figure shows the distribution of risk tolerance scores for respondents aged 60+

This result may provide some insights as to why there is a no clear consensus as to the impact of age on risk tolerance. Given there is such a wide range of RTS to be found within this age group, the results could be sample dependent and a sufficiently large sample may be necessary to avoid bias.

Table 3.4 Risk Tolerance Score Summary for Respondents Aged Over 60

Panel A: Risk Tolerance Score for all 60+ investors by Sample, Gender and Marital Status

	All	Males	Females	Married	Unmarried
Mean	51.02	53.20	45.74	51.61	48.03
Median	51.00	53.00	45.00	51.00	47.00
Maximum	91.00	91.00	81.00	91.00	90.00
Minimum	20.00	20.00	21.00	20.00	21.00
Std. Dev.	11.64	11.34	10.60	11.50	11.86

Panel B: Risk Tolerance Score by Education-Based Subgroups

Education	DNC*	High School	Trade/Diploma	University
Mean	47.34	47.97	51.20	54.96
Median	46.00	48.00	50.00	55.00
Maximum	83.00	82.00	90.00	91.00
Minimum	20.00	21.00	22.00	21.00
Std. Dev.	11.51	11.16	11.45	11.01

Panel C: Risk Tolerance Score by Income-Based Subgroups

Income Band	< \$30,000	\$30,000-\$50,000	\$50,000-\$100,000	\$100,000-\$200,000	>\$200,000
Mean	47.11	51.37	55.85	57.70	56.17
Median	47.00	52.00	55.00	58.00	56.00
Maximum	82.00	83.00	90.00	91.00	83.00
Minimum	20.00	20.00	25.00	26.00	31.00
Std. Dev.	10.67	10.63	11.47	12.02	10.95

Panel D: Risk Tolerance Score by Net Asset-Based Subgroups

Net Asset Band	< \$50,000	\$50,000-\$150,000	\$150,000-\$500,000	\$500,000-\$1,000,000	>\$1,000,000
Mean	50.70	45.64	47.66	52.03	56.72
Median	49.00	45.00	47.00	51.00	56.00
Maximum	82.00	85.00	89.00	88.00	91.00
Minimum	28.00	25.00	20.00	22.00	22.00
Std. Dev.	13.25	10.94	11.57	10.68	10.62

Note: * DNC – did not complete high school.

All of these RTS pairs are significantly different except the average RTS between:

(1) DNC and High School

(2) The following income bands

\$50,000-\$100,000   \$100,000-\$200,000   >\$200,000

(3) The following net asset bands

< \$50,000   \$50,000-\$150,000

A comparison of the RTS for these predominantly retired individuals to that of the whole sample (Table 3.3) reveals that their risk tolerance is lower across all demographic groupings. Beyond this general observation, the same patterns are observed in terms of gender, education and income as were found across the entire database. Two notable exceptions are: First, the RTS of married 60+ investors is higher than those who are unmarried which is the opposite of the trend for the full sample discussed in Section 3.3. Second, the U-Shaped trend in the RTS across asset-based subgroupings is asymmetric in this case. Panel D of Table 3.4 reveals that RTS falls and then increases as assets levels rise, which is consistent with the trend (identified in unreported results) for the full dataset. The asymmetry exists in that the RTS increases to 56.72 in the case of investors with assets of >$1,000,000 which is statistically higher than (at the 5% level of significance) the RTS of those individuals in the lowest asset grouping (50.70). Across the whole sample, these two average RTS values were closer in value (61.34 and 60.56 for the lowest and highest groupings respectively). There are sufficient observations to suggest that this anomaly is not a function of sample size, but no obvious reason exists for this outcome.

The impact of the various demographic variables on RTS for respondents aged over 60 may be formally assessed by estimating equation 3.1 for this subgroup of our data. The regression output is summarised in Table 3.5 and the coefficients relating to the gender, number of dependents and marital status are substantively unchanged to those observed in Table 3.3. A notable feature of the data is the relationship between RTS and age: in contrast to the results for the full dataset, the coefficient for the age variable (α_2) is negative and significant and the coefficient for the quadratic age variable (α_3) is positive and significant, indicating that RTS for this group decreases at a decreasing rate, rather than the increasing rate which characterises the full dataset. However, a minimum RTS is reached at age 75. Another interesting feature of this data relates to the nonsignificance of the completed high school education variable (D_{EDU2}), the \$30,000 - \$50,000 (D_{INC2}) and the >\$200,000 (D_{INC5}) income variables. Further, a significant negative relationship between two of the net asset dummy variables and RTS is found in contrast to the positive relationship estimated for the entire sample.

Table 3.5 Regression of Financial Risk Tolerance on Demographic Variables for Respondents Aged Over 60

Variable	Coefficient	Std. Error	t-statistic	p-value
α_0	158.3557	43.6252	3.63	0.000
D_{FEM}	-5.5949	0.5319	10.52	0.000
AGE	-2.9099	1.2817	2.27	0.023
AGE^2	0.0195	0.0094	2.08	0.038
NDEP	-0.2446	0.3004	0.81	0.416
$D_{MARRIED}$	-1.6558	0.7951	2.08	0.037
D_{EDU2}	0.0725	0.6957	0.10	0.917
D_{EDU3}	1.2995	0.6495	2.00	0.046
D_{EDU4}	3.1827	0.6753	4.71	0.000
D_{INC2}	0.2839	0.6466	0.44	0.661
D_{INC3}	2.0641	0.8119	2.54	0.011
D_{INC4}	2.4833	1.1817	2.10	0.036
D_{INC5}	-0.7106	1.9988	0.36	0.722
D_{CINC2}	2.6323	0.7208	3.65	0.000
D_{CINC3}	3.1202	0.8134	3.84	0.000
D_{CINC4}	2.7465	1.0883	2.52	0.012
D_{CINC5}	4.0693	1.7557	2.32	0.021
D_{NASS2}	-3.9618	1.4806	2.68	0.008
D_{NASS3}	-3.3609	1.2862	2.61	0.009
D_{NASS4}	-0.9039	1.3103	0.69	0.490
D_{NASS5}	1.8870	1.351	1.40	0.163
Adjusted R-squared = 0.2128	F-stat = 33.25 (P-value = 0.000)			

Wald Tests of Coefficient Equality:	($D_{INC2} = D_{INC3} = D_{INC4} = D_{INC5}$)	P-value = 0.032
	($D_{INC4} = D_{INC5}$)	P-value = 0.091
	($D_{CINC2} = D_{CINC3} = D_{CINC4} = D_{CINC5}$)	P-value = 0.767
	($D_{NASS2} = D_{NASS3} = D_{NASS4} = D_{NASS5}$)	P-value = 0.000
	($D_{NASS4} = D_{NASS5}$)	P-value = 0.000

This table presents a summary of the estimated regression output for the equation fitted to a restricted dataset of respondents aged 60+:

$$RTS_i = \alpha_0 + \alpha_1 D_{i,FEM} + \alpha_2 AGE_i + \alpha_3 AGE^2 + \alpha_4 NDEP_i + \alpha_5 D_{i,MARRIED} +$$
$$\sum_{g=EDU_2}^{EDU_4} \alpha_g D_{i,g} + \sum_{h=INC_2}^{INC_5} \alpha_h D_{i,h} + \sum_{j=CINC_2}^{CINC_5} \alpha_j D_{i,j} + \sum_{k=NASS_2}^{NASS_5} \alpha_k D_{i,k} + \varepsilon_i$$

where RTS_i is the FinaMetrica RTS for individual *i*, Age is the age expressed in years, NDEP is the number of financial dependents, D are dummy variables for gender (FEM), marital status (MARRIED), education (EDU), income (INC) and combined income (CINC), and α are the coefficients to be estimated.

3.3.4. Marital Status and Risk Tolerance

Marital status is a potentially important demographic which impacts on the preferred level of risk in the investment process. As discussed in Chapter 2, the relationship between marital status and risk tolerance remains unresolved: although there is some evidence that single investors are more risk tolerant, a number of studies has failed to identify any significant relationship (McInish, 1982; Masters, 1989; and Haliassos and Bertaut, 1995). The exploratory study reported in Chapter 2 found a negative relationship between marital status and risk tolerance: in contrast, the evidence from the examination of the larger database, provided in Table 3.3 and discussed in Section 3.3.2, suggests marriage is a significant determinant of RTS. Accordingly, it is worthwhile considering this result in more detail using an extended analysis of the FinaMetrica database. Table 3.6 presents a summary of the RTS by marital status and various demographics.

Table 3.6 Risk Tolerance Score Summary for Married Respondents

Panel A: Risk Tolerance Score by Marital Status and Gender

	Married	Unmarried	Married Males	Unmarried Males	Married Females	Unmarried Females
Mean	58.83	60.29	61.00	64.01	53.97	55.72
Median	59.00	60.00	61.00	64.00	54.00	56.00
Maximum	95.00	95.00	95.00	95.00	93.00	91.00
Minimum	20.00	21.00	20.00	23.00	20.00	21.00
Std. Dev.	12.65	13.43	12.26	12.83	12.15	12.73

Panel B: Risk Tolerance Score by Marital Status and Education-Based Subgroups

	Married				Unmarried			
Education	DNC*	High Sch.	Trade/Dip	University	DNC*	High Sch.	Trade/Dip	University
Mean	52.43	55.03	58.13	61.71	50.41	55.76	59.33	63.06
Median	52.00	55.00	58.00	62.00	48.00	56.00	59.00	63.00
Maximum	91.00	92.00	95.00	95.00	89.00	92.00	94.00	95.00
Minimum	20.00	21.00	20.00	24.00	21.00	21.00	25.00	21.00
Std. Dev.	13.02	12.46	12.77	11.72	13.36	13.85	13.57	12.34

Panel C: Risk Tolerance Score by Marital Status and Income-Based Subgroups

	Married					Unmarried				
Income Band	< $30,000	$30,000-$50,000	$50,000-$100,000	$100,000-$200,000	>$200,000	< $30,000	$30,000-$50,000	$50,000-$100,000	$100,000-$200,000	>$200,000
Mean	51.23	56.58	61.13	64.71	63.79	55.55	59.36	63.62	62.35	65.11
Median	51.00	56.00	61.00	65.00	63.50	55.00	59.00	63.00	63.00	66.00
Maximum	93.00	93.00	94.00	95.00	95.00	92.00	93.00	95.00	95.00	95.00
Minimum	20.00	20.00	20.00	26.00	27.00	21.00	22.00	23.00	26.00	31.00
Std. Dev.	11.67	12.06	11.86	11.50	10.98	13.34	13.43	12.22	11.92	13.92

Note: * DNC – did not complete high school.
All of these RTS scores are significantly different except the RTS for married and unmarried individuals with INC >$2m

All of the reported RTS scores are significantly different except the RTS for married and unmarried individuals with income greater than \$200,000 (Panel C). Panel A presents a summary of our data classified by marital status and gender. Married individuals are found to exhibit a lower RTS and gender does not impact on this trend. Panel B considers the RTS of individuals by marital status and education and Panel C presents information on the RTS classified by marital status and income. Comparing the RTS of married and unmarried individuals across these various demographics reveals no obvious differences.

As a final step in investigating whether marriage impacts on RTS, Tables 3.7 and 3.8 present the estimation output of our regression based model of the determinants of RTS (equation 3.1) applied to married survey respondents and unmarried survey respondents respectively.

Table 3.7 Regression of Financial Risk Tolerance on Demographic Variables for Married Respondents

Variable	Coefficient	Std. Error	t-statistic	p-value
α_0	64.0951	1.5159	42.28	0.000
D_{FEM}	-6.1047	0.2433	-25.08	0.000
AGE	-0.1107	0.0658	-1.68	0.092
AGE^2	-0.0021	0.0006	-3.13	0.001
NDEP	-0.1225	0.0780	-1.56	0.116
D_{EDU2}	0.3445	0.4100	0.84	0.400
D_{EDU3}	1.4212	0.3854	3.68	0.000
D_{EDU4}	2.3884	0.3805	6.27	0.000
D_{INC2}	1.0598	0.3342	3.17	0.001
D_{INC3}	2.8119	0.3593	7.82	0.000
D_{INC4}	4.3958	0.4460	9.85	0.000
D_{INC5}	2.8315	0.6789	4.17	0.000
D_{CINC2}	1.1273	0.4694	2.40	0.016
D_{CINC3}	2.4067	0.4552	5.28	0.000
D_{CINC4}	3.3554	0.5013	6.69	0.000
D_{CINC5}	3.7085	0.6417	5.77	0.000
D_{NASS2}	0.6225	0.4675	1.33	0.183
D_{NASS3}	0.3661	0.4338	0.84	0.398
D_{NASS4}	2.0632	0.4719	4.37	0.000
D_{NASS5}	2.8158	0.5118	5.50	0.000
Adjusted R-squared = 0.2420	F-stat = 215.89 (P-value = 0.000)			

This table presents a summary of the estimated regression output for the equation fitted to a restricted dataset of married respondents:

$$RTS_i = \alpha_0 + \alpha_1 D_{i,FEM} + \alpha_2 AGE_i + \alpha_3 AGE^2 + \alpha_4 NDEP_i + \sum_{g=EDU_2}^{EDU_4} \alpha_g D_{i,g} + \sum_{h=INC_2}^{INC_5} \alpha_h D_{i,h} + \sum_{j=CINC_2}^{CINC_5} \alpha_j D_{i,j} + \sum_{k=NASS_2}^{NASS_5} \alpha_k D_{i,k} + \varepsilon_i$$

where RTS_i is the FinaMetrica RTS for individual i, Age is the age expressed in years, NDEP is the number of financial dependents, D are dummy variables for gender (FEM), marital status (MARRIED), education (EDU), income (INC) and combined income (CINC), and α are the coefficients to be estimated.

Table 3.8 Regression of Financial Risk Tolerance on Demographic Variables for Unmarried Respondents

Variable	Coefficient	Std. Error	t-statistic	p-value
α_0	57.4524	2.0176	28.47	0.000
D_{FEM}	-6.3104	0.4093	15.42	0.000
AGE	0.1844	0.0972	1.90	0.058
AGE^2	-0.0054	0.0011	5.06	0.000
NDEP	-0.3780	0.2311	1.64	0.102
D_{EDU2}	2.2355	0.9188	2.43	0.015
D_{EDU3}	4.1150	0.9149	4.50	0.000
D_{EDU4}	5.9265	0.8663	6.84	0.000
D_{INC2}	0.7175	0.5338	1.34	0.179
D_{INC3}	3.4654	0.5775	6.00	0.000
D_{INC4}	1.5450	0.5723	2.70	0.007
D_{INC5}	3.9942	1.3852	2.88	0.004
D_{CINC2}	0.6850	1.2189	0.56	0.574
D_{CINC3}	-0.2572	1.3063	0.20	0.844
D_{CINC4}	1.7019	1.6748	1.02	0.310
D_{CINC5}	-0.4819	2.6974	0.18	0.858
D_{NASS2}	1.7736	0.6025	2.94	0.003
D_{NASS3}	2.2670	0.6451	3.51	0.000
D_{NASS4}	3.9164	0.8287	4.73	0.000
D_{NASS5}	5.0402	1.0066	5.01	0.000

Adjusted R-squared = 0.2363   F-stat = 58.350 (P-value = 0.000)

This table presents a summary of the estimated regression output for the equation fitted to a restricted dataset of unmarried respondents:

$$RTS_i = \alpha_0 + \alpha_1 D_{i,FEM} + \alpha_2 AGE_i + \alpha_3 AGE^2 + \alpha_4 NDEP_i + \sum_{g=EDU_2}^{EDU_4} \alpha_g D_{i,g} + \sum_{h=INC_2}^{INC_5} \alpha_h D_{i,h} + \sum_{j=CINC_2}^{CINC_5} \alpha_j D_{i,j} + \sum_{k=NASS_2}^{NASS_5} \alpha_k D_{i,k} + \varepsilon_i$$

where RTS_i is the FinaMetrica RTS for individual *i*, Age is the age expressed in years, NDEP is the number of financial dependents, D are dummy variables for gender (FEM), marital status (MARRIED), education (EDU), income (INC) and combined income (CINC), and α are the coefficients to be estimated.

Comparing the estimated coefficients of the two samples some notable differences are apparent: Firstly, all levels of education of an unmarried individual are associated with a significant monotonic increase in RTS, whereas the results for married individuals indicate that a trade/diploma level of education was required before a significant positive relationship was observed. A similar monotonic relationship between the range of net asset categories and

RTS is observed for unmarried individuals; however, married individuals must record a level of net assets of at least $500,000 before a significant relationship with RTS is observed. On the other hand, while all income categories were individually significant and positive for married individuals, unmarried respondents needed an income of at least $30,000 before a significant relationship was observed. Interestingly, the $100,000-$200,000 category is associated with the largest increase in RTS (4.4 points) for married respondents but with the smallest increase (1.6 points) in RTS for unmarried respondents.

Thus, while the data provides support for the notion that single investors are more risk tolerant, it contrasts with the existing body of evidence (McInish, 1982; Masters, 1989; and Haliassos and Bertaut, 1995) which finds that marital status has no material impact on investment decisions.

3.3.5. Education and Wealth

One interesting issue that the data enables exploration of is the relationship between education and wealth. For this generation of investors, a university degree was far less common compared to current trends and at the time, the general perception was that a tertiary education would secure a financial future. The data enables exploration of the relationship between respondents answers to their level of assets and completed education. A cross tabulation summary of the data is presented in Table 3.9 and reveals that as expected, almost half (48.59%) of elderly millionaires are university educated and only a small fraction did not complete high school (9.12%). Of those individuals who fall into the lowest asset sub-grouping, the majority did not complete any education beyond high school. A trend is apparent across the three middle asset sub-groupings as a higher level of education is associated with a higher level of net assets, ie. 34.55% of those with assets of $50,000 - $100,000 did not complete high school, 31.57% of those with assets of $150,000 - $500,000 completed trade school or a diploma, and 35.29% of those with assets of $500,000 - $1,000,000 completed university. Thus, the evidence suggests that the wealth of retiring-age individuals reflects their level of education.

Table 3.9 Cross Tabulation of Net Assets and Education for Respondents Aged Over 60

Net Asset Band	< $50,000	$50,000-$150,000	$150,000-$500,000	$500,000-$1,000,000	>$1,000,000
Panel A: No. of Observations					
DNC*	4	57	209	90	55
High Sch.	11	39	199	147	84
Trade/Dip	5	46	280	205	171
University	3	23	199	241	293
Panel B: Percentage of Responses					
DNC*	17.39	34.55	23.56	13.18	9.12
High Sch.	47.83	23.64	22.44	21.52	13.93
Trade/Dip	21.74	27.88	31.57	30.01	28.36
University	13.04	13.94	22.44	35.29	48.59

Note: * DNC – did not complete high school.

3.4. Summary and Conclusion

The aim of this chapter is to investigate the relationship between demographic factors and financial risk tolerance. The study employs a large database that contains a psychometrically derived risk tolerance score (RTS) measured by FinaMetrica. While it is found that peoples self-assessed risk tolerance and FinaMetrica RTS generally accord, there is considerable variation with a tendency for respondents to under-estimate their risk tolerance. This suggests that financial planners who rely largely on subjective assessments of risk tolerance run the risk of suggesting inappropriate, and in the majority of cases overly conservative, investment strategies for their clients.

The analysis of the relationship between participant demographics and risk tolerance reveals that gender, income and wealth are significantly associated with financial risk tolerance. A detailed investigation of the relationship between risk tolerance and age as well as marital status was also performed. The results suggest that a negative relationship between age and risk tolerance exists which, while in line with generally held industry beliefs, contradicts some of the more recent research findings. Further, it was found that the relationship between age and risk tolerance exhibits a significant nonlinear structure. Finally, a negative relationship between marital status and risk tolerance was found.

As suggested above, assessment of an investor's risk profile is a highly influential factor in the construction of an appropriate investment portfolio. This research, in providing support for the widely held view that women have lower risk tolerance than men and that, at least in a cross-sectional sense, age has an inverse, though non-linear, relationship with risk tolerance, has significant implications for the funds management industry: as the baby boomer cohort ages and moves into retirement we could expect to see demand shift away from the relatively more risky growth asset classes towards the less risky income asset classes, reflecting the decline in risk tolerance associated which increasing age. Moreover, this effect would be compounded by the greater life expectancy of women: as the population ages the gender composition will shift in favour of women, who on average have lower risk tolerance. Thus, the changing age and gender demographics of the population will provide a duel force for change in the composition of the overall demand for investment products.

The relationship between gender and risk tolerance is explored in greater detail in Chapter 4.

Chapter 4: Women and Risk Tolerance in an Aging World

"While boys outnumber girls in all countries, gender differences in mortality eventually produce a changing sex balance within a population. By age 30 or 35, women start to outnumber men, and the absolute female advantage increases with age. Elderly women greatly outnumber elderly men in most nations, and therefore the health and socioeconomic problems of the elderly are, to a large extent, the problems of elderly women." (Kinsella and Gist, 1998)

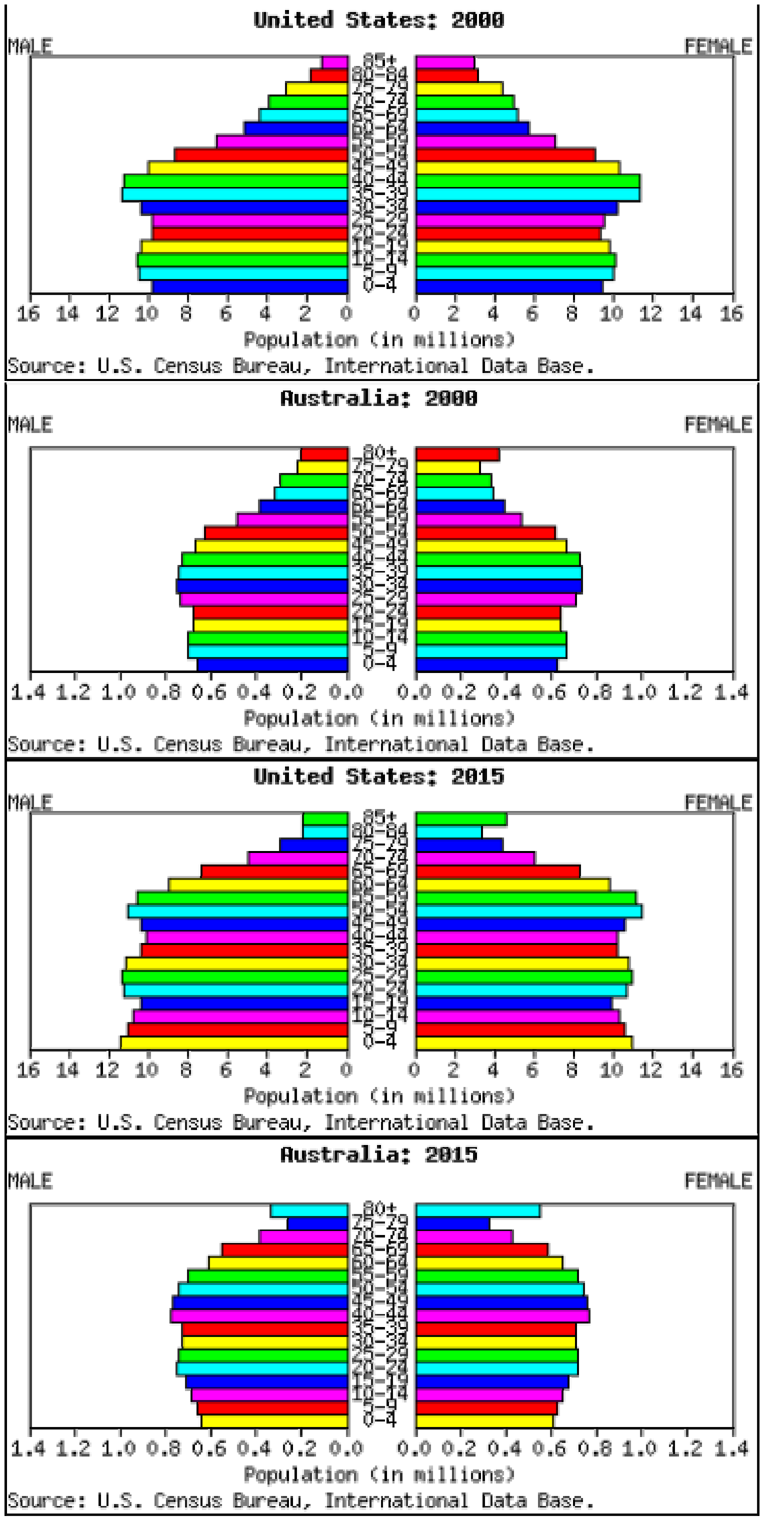
4.1. Introduction

The above quotation from a U.S. Census Bureau report draws attention to looming health and welfare problems arising from demographic aging of populations around the world (Kinsella and Gist, 1998). Health and welfare issues have understandably captured the attention of researchers and governments because of their fiscal implications. One issue that has received relatively little attention, however, is the implications for financial markets of a population that is ageing and becoming more predominantly female. If women have different attitudes to investing than men, then a shift in the control of personal wealth to women could be expected to impact not just upon the investment management industry, but upon the welfare of the investors themselves. In particular, the influence of women's risk tolerance on their investment decisions will be an important determinant of their financial well-being in retirement.

The truth of this conjecture depends on whether women display a different attitude towards financial risk-taking relative to men. While stereotypical beliefs about gender differences are prevalent, there are now a number of studies that suggest women may be more risk averse than men in general business decision-making, and specifically in financial decision-making. Why is this significant? Studies in the US have found that while only 12% of women who have partners have sole responsibility for the family's investments, the greater longevity of females as well as the increasing divorce rate, mean that nine out of ten women will find themselves responsible for their family's finances and investments (Kover, 1999). Moreover, a 1997 report by the Bank of America found that the average age of widowhood for an American female is 56 years (Aguilar 2001). Given these factors, it should not come as a surprise that the report suggested that women had control of about 75% of total personal wealth in America. The implications of this are most apparent in the managed funds industry: as the baby boomer bulge moves through the age profile, the gender composition will shift further in favor of women.

Chapters 2 and 3 presented evidence that the women respondents did differ from men in their attitude to financial risk taking. This chapter contributes to the literature by further examining this finding, through further analysis of the large database used in the research described in Chapter 3 (psychometrically-derived risk profiles for around 20,000 adult Australians). As much of the extant literature uses US data, the use of Australian data provides an important response to the concerns raised by Jiankoplos and Bernasek (1998) that much of what we know about investor risk tolerance could be country specific. To the extent that Australia shares a number of demographic and cultural similarities with other developed countries, the results of this study are relevant for these countries as well. For example, demographic similarities are apparent in the population pyramids depicted in Figure 4.1, with both Australia and the United States forecast to experience an increase in the elderly female segment of the population.

Figure 4.1 Population Pyramids



From a somewhat different perspective, data from the U.S. Census Bureau reproduced in Panel A of Table 4.1 shows the impact of the baby boomers on the populations of developed countries outside Western Europe. Again, each country is forecast to experience significant increases in its elderly population, with the proportion of the population aged 65 and over increasing by, for example, 59 percent in the United States and 70 percent in Australia (from the year 2000 to 2030).

Table 4.1 Aging Population Projections for United States, Australia, Canada and New Zealand

	Over 65 Years of Age			Over 80 Years of Age		
Country	2000	2015	2030	2000	2015	2030
Panel A: Percent of Population						
United States	12.6	14.7	20.0	3.3	3.8	5.3
Australia	12.4	15.8	21.1	3.0	4.1	6.0
Canada	12.7	16.1	22.9	3.1	4.3	6.2
New Zealand	11.5	13.7	17.8	2.9	3.5	5.0
Panel B: Sex Ratio of Population[a]						
United States	71	79	80	50	66	61
Australia	78	82	81	55	62	66
Canada	74	77	79	52	56	61
New Zealand	77	79	79	53	60	62

Source: U.S. Census Bureau 2000
[a] Sex ratio is defined as the number of men per 100 women in a given population or age category.

While the proportion of elderly in the population is increasing we also need to examine whether there are expected to be any significant changes in the gender composition of the population over 65. This is done through a simple measure of gender composition, the sex ratio, defined by the U.S. Census Bureau as the number of men per 100 women in a given population or age category. In Panel B of Table 4.1 it is apparent that while each country listed is expected to experience some increase in the ratio over the period 2000 – 2030, the sex ratios peak at around 80. For the very old, those aged 80 and over, there is a similar pattern of increase although the ratios are much more in favor of women initially, ranging from 50-55 in 2000 to 61-66 in 2030.

The analysis undertaken in this chapter proceeds as follows. Building on the overview of research into the determinants of financial risk tolerance contained in Chapters 2 and 3, a review of research specifically relating to risk tolerance and gender is presented in Section 4.2. Regression analysis is used to examine the determinants of financial risk tolerance in the database and indicates that, consistent with the results of the research in Chapter 3, all of the demographic characteristics are found to be significant. The role of gender is then considered by focusing on the differential impact of gender on each of the demographic factors. Finally, a test for the presence of non-linearities in our relationships is undertaken.

.

4.2. Gender and Risk Tolerance

As noted in Chapter 2 (Section 2.1), gender is frequently tested as a determinent of risk tolerance and females typically show a lower preference for risk than males, although the research in this area is by no means uniform.

Slovic (1966) documents what is considered to be the prevalent belief in western culture that men should, and do, take greater risks than women. Early psychological research on differences in decision-making generally was consistent with this belief. Eagly (1995) surveys research from the general psychology literature into gender differences relating to behavior, attitudes, cognitive ability, decision making and personality traits in the context of risk and decision-making and concluded that the bulk of the research suggests women are less aggressive, less confident, more cautious and possessing inferior leadership and problem solving abilities. However, these conclusions are not unanimous: Johnson and Powell (1994) reviewed earlier literature specifically on business decision-making and found the results to be ambiguous. For example, Powell (1990) found no significant differences in managers' decision-making style, and Masters and Meier (1988) were unable to differentiate between the risk-taking propensity of male and female entrepreneurs [although more recently Verheul, Risseeuw and Bartelse (2002) found gender differences in a range of other dimensions - in path traveled to entrepreneurship, strategy and type of leadership].

Schubert, Brown, Gysler and Brachinger's (1999) research suggests that gender-specific risk behavior is due more to contextual factors than a general trait, a finding consistent with Hudgens and Fatkin's (1985) experimental evidence that gender differences occur only in situations where the probability of success is low. In a similar vein, Siegrist, Cvetkovich and Gutscher (2002) examined biases in predicting the risk preferences of other people. While reporting that both women and men overestimated males' risks preferences, their research suggests that participants' predictions were influenced by knowledge about risk preferences incorporated in gender stereotypes and by their own feelings.

Another strand of research sought evidence of gender differences in financial literacy and attitudes towards money. Prince (1992) found that while both sexes saw money as closely linked with esteem and power, males were more prone to feel more involved and competent in money handling, and more prepared to take risks to build wealth. More recently, Chen and Volpe (2002) found statistically significant differences between male and female college students' financial literacy. Echoing Prince's (1992) findings, they found female students less interested and willing to learn about personal finance topics and less confident in dealing with these topics. Similarly, Stinerock, Stern and Solomon (1991) analyzed consumers use of professional financial advisers and found women had a higher degree of anxiety and lower risk preference when making financial decisions, and a stronger desire to use financial advisers. When examining both general and expert investors, Estes and Hosseini (1988) found females less confident in financial decision making, with gender the most important explanatory factor affecting confidence, ahead of age, experience, education, knowledge and asset holdings. Barber and Odean (2001) use gender as a proxy for overconfidence and find men trade more and perform worse than women.

In a related vein, Hawley and Fujii (1993) drew on data from the 1983 Survey of Consumer Finances which included questions asking respondents to state their preferences for taking financial risks. They found female heads of household were the most risk averse followed by single women. Interestingly, married women reported the lowest risk aversion.

Outside of the United States, Clark-Murphy and Gerrans (2001) examined survey responses from 2,399 Australian university staff and found women significantly more likely than men to consider themselves to have a lower level of knowledge, and more likely to seek advice from a financial advisor.

Turning to evidence of gender differences in financial decision-making, there are a number of studies which examine the composition and risk profile of an individual's entire portfolio. Early research by Cohn et al. (1975) and Lewellen, Stanley, Lease and Schlarbaum (1978) found that gender was significantly related to the proportion of risky assets held, and that female investors hold less risky portfolios. Riley and Chow (1992) analyzed asset allocation data provided by the Survey of Income and Participation and found some evidence that women are slightly more risk averse than men. The US Federal Reserve Board sponsored triennial Survey of Consumer Finances (SCF) has enabled a number of researchers to explore the issue of stated preference and revealed preference by examining the relationship between stated risk aversion, gender and asset allocation. For example, Schooley and Worden (1996) examined the 1989 SCF and compared household's reported willingness to take financial risk to the riskiness of their portfolios, measured as the proportion of risky assets to wealth. They found that overall households did allocate portfolio holdings consistent with their stated attitudes toward risk. They also found that the portfolios of households headed by females had significantly lower ratios of risky assets to wealth, although a coding procedure used in the creation of the data set meant that the extent of this gender difference could not be fully ascertained.

Jiankoplos and Bernasek (1998), using the same survey data found that as wealth increases, the proportion of wealth held as risky assets increased by a smaller amount for single women than for single men and married couples. Interestingly, they report that about 60% of female respondents and 40% of male respondents stated they were not prepared to accept *any* financial risk. Bajtelsmit et al.(1999), again using the 1989 SCF, investigated pension allocations as part of the household's overall portfolio, finding significant gender differences in the overall allocation of wealth, with women exhibiting greater relative risk aversion in their allocation of wealth into defined contribution pension assets. Halek and Eisenhaeur (2001) used life insurance data to estimate relative risk aversion coefficients and then examined these in relation to demographic characteristics. They found men were less risk averse than women and that the difference in risk aversion across gender was highly significant.

Pension schemes that give the beneficiary some degree of control over asset allocation have enabled researchers to further explore the impact of gender. Bajtelsmit and Vanderhai (1997) examined the asset allocation decisions of a sample of nearly 17,000 management employees of a large United States employer. These employees were able to select from a choice of five investment alternatives offering different risk/return characteristics. It was found that women were significantly more likely to invest in fixed income securities and less likely to invest in employer stock. Hinz, McCarthy and Turner (1997) used data from the Thrift Savings Plan for United States Federal Government employees both found that women allocated a smaller proportion of their funds to equities than did men. Sunden and Surette (1998), using data from the 1992 and 1995 SCF, and after controlling for a range of demographic, financial and attitudinal characteristics, report that gender and marital status interact to significantly affect how individuals choose to allocate assets in defined-contribution plans: single women and married men were less likely than single men to choose the riskier portfolio option. Bernasek and Shwiff (2001) found that among university faculty, gender was the most significant factor in explaining the proportion of the pension invested in risky assets, with women more conservative investors than men. Interestingly, when interactive effects were added to the model, it was found that married and cohabiting women and men reacted in different ways to the attitudes towards risk of their partners: men were prepared to take on more risk than their partners while women were prepared to take less risk.

Barber and Odean (2001) examine the common stock portfolio holdings of men and women and find men invest in riskier positions than women when measured against four risk measures (portfolio volatility, individual stock volatility, beta and size). Dwyer, Gilkeson and List (2002) using data from a survey of 2000 randomly selected mutual fund investors, found that women exhibited less risk taking than men in their mutual fund investment decisions. Importantly, the impact of gender was significantly weakened when investor-specific financial investment knowledge was controlled for in the analysis, suggesting that the apparently lower risk tolerance of women is not an inalterable trait.

Researchers have also placed professional investors under the spotlight. Olsen and Cox (2001) investigate gender differences in attitudes towards risk for professionally trained investors. It was found that women investors weight risk attributes, such as possibility of loss and ambiguity, more heavily than their male colleagues. In addition, women tend to emphasize risk reduction more than men in portfolio construction. While gender differences appear to influence perceptions of risk and recommendations to clients, these differences tend to be the most significant for assets and portfolios at risk extremes. Bliss and Potter (2002) explore whether gender affects fund manager performance and/or behavior, in particular whether female fund managers are more risk-averse and less confident. Their exploration of whether equity mutual funds managed by women differed systematically in performance or operationally from those managed by men produced negative findings. Atkinson, Baird and Frye (2003) examined fixed income mutual fund managers and failed to find significant differences in terms of performance, risk or other fund characteristics. The difference appeared to be in the behavior of investors, with lower net asset flows into funds managed by women, suggesting gender stereotypes affect investor decision making.

4.3. Description of Survey Sample

As in Chapters 2 and 3, the data for the research in this chapter was provided by FinaMetrica. Accompanying the risk tolerance test is a set of eight demographic questions dealing with age, gender, postcode, education, income, marital status, dependents and net assets. In the case of education, income (individual and combined) and net assets; ordered categorical variables are created and the details of these are provided in Table 4.2.

The data sample comprised 20,353 Australian respondents who completed the survey in May 1999 – February 2002.[20]

[20] Consistent with the approach noted in Chapters 2 and 3, and following consultation with FinaMetrica, respondents who recorded their age as less than 20 years or older than 80 years, and respondents who generated a RTS outside the range 20-95 were omitted from the analysis, as such responses were not considered plausible. A total of 356 respondents were excluded on these criteria.

Table 4.2 Summary of Ordered Categorical Variables

Ordered Categorical Variable Value	Education (EDU)[a]	Income (INC)[b]	Combined Income (CINC)[c]	Net Assets (NASS)[d]
1	Did not complete high school	Under $30,000	Under $30,000	Under $50,000
2	Completed high school	$30,000 - $50,000	$30,000 - $50,000	$50,000 - $150,000
3	Trade or diploma qualification	$50,000 - $100,000	$50,000 - $100,000	$150,000 - $500,000
4	University degree or higher qualification	$100,000 - $200,000	$100,000 - $200,000	$500,000 - $1,000,000
5	na[e]	Over $200,000	Over $200,000	Over $1,000,000

[a] The highest education level attained, or the closest equivalent.
[b] The income bracket for the respondent's personal before-tax income (having in mind income from all sources – work, investment, family and government).
[c] If married (or defacto), the income bracket for the respondent's combined before-tax income.
[d] The respondent's own net assets, including the family home and other personal-use assets, minus any amounts owed (if married or de facto, the respondent includes their share of jointly owned assets).
[e] 'not applicable'

A summary of the demographic information for the investors captured in this database is presented in Table 4.3. Unfortunately, not all of the respondents who completed the survey and received an assessment of their financial risk tolerance also completed all of the demographic questions. As such, the number of observations for each demographic will be less than the total size of the RTS database. For example, 2726 respondents did not indicate their gender which reduced the sample to 17,627 comprising 11566 males (65.62%) and 6061 females (34.38%). More specifically, Panel A of Table 4.3 reveals that the majority of the survey respondents are married (76.82%). Panel B shows that proportionately more males (52.47%) than females (45.39%) had a university degree or higher qualification.

Table 4.3 Dataset Partitioning Summary – Observation Counts

	Males						Females						Grand Total
	Age (years)					Total	Age (years)					Total	
	<=30	31-40	41-50	51-60	>60		<=30	31-40	41-50	51-60	>60		
Panel A: Marital Status													
Unmarried	997	470	325	254	162	2208	597	291	328	327	234	1777	3985
Married	728	1937	2327	2667	1471	9130	536	922	1070	1099	451	4078	13208
Total	1725	2407	2652	2921	1633	11338	1133	1213	1398	1426	685	5855	17193
Panel B: Education[a]													
Edu1	31	110	154	238	254	787	29	70	111	214	156	580	1367
Edu2	200	254	330	476	252	1512	148	207	338	402	223	1318	2830
Edu3	276	599	726	897	525	3023	159	290	316	329	156	1250	4273
Edu4	1210	1417	1404	1275	569	5875	790	629	607	457	134	2617	8492
Total	1717	2380	2614	2886	1600	11197	1126	1196	1372	1402	669	5765	16962
Panel C: Income[b]													
Inc1	307	116	131	356	543	1453	287	310	386	575	380	1938	3391
Inc2	527	377	403	600	429	2336	436	300	421	342	143	1642	3978
Inc3	577	969	1068	1023	371	4008	279	344	348	281	73	1325	5333
Inc4	175	600	636	547	144	2102	39	134	115	77	15	380	2482
Inc5	30	228	326	264	63	911	6	34	37	29	7	113	1024
Total	1616	2290	2564	2790	1550	10810	1047	1122	1307	1304	618	5398	16208
Panel D: Combined Income[c]													
Cinc1	47	42	45	155	326	615	41	24	33	161	177	436	1051
Cinc2	90	149	152	361	377	1129	71	78	110	215	126	600	1729
Cinc3	369	678	832	966	460	3305	255	347	420	394	119	1535	4840
Cinc4	262	790	880	825	203	2960	170	324	361	249	39	1143	4103
Cinc5	52	307	420	350	81	1210	44	156	159	96	20	475	1685
Total	820	1966	2329	2657	1447	9219	581	929	1083	1115	481	4189	13408

	Males						Females						Grand Total
	Age (years)					Total	Age (years)					Total	
	<=30	31-40	41-50	51-60	>60		<=30	31-40	41-50	51-60	>60		
Panel E: Net Assets[d]													
Nass1	856	237	69	32	11	1205	610	140	46	30	11	837	2042
Nass2	466	499	254	144	96	1459	262	265	179	112	62	880	2339
Nass3	291	1004	1067	878	551	3791	183	492	585	542	284	2086	5877
Nass4	35	378	688	870	454	2425	24	158	310	391	171	1054	3479
Nass5	24	194	474	857	430	1979	13	81	197	253	107	651	2630
Total	1672	2312	2552	2781	1542	10859	1092	1136	1317	1328	635	5508	16367

[a] Education groups are classified as follows: ‘Edu1’: did not complete high school; ‘Edu2’: completed high school; ‘Edu3’: trade or diploma qualification; ‘Edu4’: university education.

[b] Income groups are classified as follows: ‘Inc1’: under $30,000; ‘Inc2’: $30,000 - $50,000; ‘Inc3’: $50,000 - $100,000; ‘Inc4’: $100,000 - $200,000; ‘Inc5’: over $200,000.

[c] Combined income groups are classified as follows: ‘Cinc1’: under $30,000; ‘Cinc2’: $30,000 - $50,000; ‘Cinc3’: $50,000 - $100,000; ‘Cinc4’: $100,000 - $200,000; ‘Cinc5’: over $200,000.

[d] Net asset groups are classified as follows: ‘Nass1’: under $50,000; ‘Nass2’: $50,000 - $150,000; ‘Nass3’: $150,000 - $500,000; ‘Nass4’: $500,000 - $1,000,000; ‘Nass5’: over $1,000,000.

Panel C shows the breakdown of respondents' personal before-tax income. It is interesting to note that although 45.47% of total respondents reported incomes below $50,000, a much greater proportion of females (66.32%) than males (35.05%) were in this category. As might be expected this disparity is reduced when combined incomes are considered: Panel D shows that 24.73% of females and 18.92% of males report combined family incomes of less than $50,000.

Finally, Panel E shows that 75.47% of males and 68.83% of females have more than $150,000 in net assets, with both groups recording their highest proportions in the $150,000 and $500,000 bracket. Taken in conjunction with the age information discussed earlier, this tends to suggest that the typical survey respondent is nearing or at retirement and is asset rich and income poor.

4.4. Empirical Framework

In order to test the determinants of risk tolerance, a number of different demographic factors may be considered. It is possible to quantify the effect of each of these demographic characteristics on the risk tolerance of an individual using statistical analysis. The model to be tested in this paper hypothesizes that the RTS for individual *i* is a function of each of these demographic characteristics, i.e.:

$$\begin{aligned} RTS = \alpha_0 + \alpha_1 DFEM + \alpha_2 DMARR + \alpha_3 NDEP + \alpha_4 AGE + \alpha_5 EDU \\ + \alpha_6 INC + \alpha_7 (DMARR * CINC) + \alpha_8 NASS + \varepsilon \end{aligned} \tag{4.1}$$

where:

RTS is the financial risk tolerance score for each surveyed individual provided by FinaMetrica based on the answers to their Risk Tolerance Questionnaire and takes a value somewhere in the range between zero to 100 and;

DFEM is a dummy variable that signifies a respondent is female.

DMARR is a dummy variable that takes a value of unity if the respondent is married (legally or defacto).

NDEP is the number of people in the family whom are financially dependent on the respondent.

AGE is the age (in years) of the respondent.

EDU is an ordered categorical variable representing the educational background of respondents, 1 (4) representing the minimum (maximum) education level. Table 4.2 defines the four categories.

INC is an ordered categorical variable representing the income of respondents, 1 (5) representing the minimum (maximum) income level. Table 4.2 defines the five categories.

CINC is an ordered categorical variable representing the combined income of respondents (and their partner), 1 (5) representing the minimum (maximum) income level. Table 4.2 defines the five categories.

NASS is an ordered categorical variable representing the net assets of respondents, 1 (5) representing the minimum (maximum) income level. Table 4.2 defines the five categories.

The correlations between all these potential independent variables are reported in Table 4.4. As might be expected, the strongest correlation (0.7940) is found between the respondent’s income and the respondent’s combined family income. The relationships between the respondent’s net assets and age (0.5422) and net assets and combined family income (0.4012) exhibit moderate positive associations while weaker positive correlations are observed between marriage and the number of dependents (0.3576), marriage and combined family income (0.3461) and marriage and the respondents net assets (0.3627). Similarly weaker positive correlations are observed between the respondent’s income and net assets (0.3433) and income and education (0.3358). Focusing on the dummy variable for gender (DFEM), all the correlation coefficients between this variable and the other independent variables (with the exception of the dummy variable for marriage (DMARR)) indicate weak negative relationships. Interestingly, the relationship between the respondent’s gender and their income displays the strongest negative correlation (-0.3210), indicating a tendency for female respondents to have lower income. Table 4.4 provides some comfort that multicollinearity is unlikely to affect the estimation of the coefficients in the regression equations.[21]

The strongest correlation coefficient (0.7940), between the respondent's income and the respondent's combined family income, is insufficiently high to indicate severe multicollinearity between these two independent variables. In any case these two variables do not enter the regression together as such – referring to equation (4.1) CINC is included interactively with DMARR. Additionally, the absence of high R^2 values in company with low t-statistic values for the regression results also supports this conclusion. Notwithstanding this, the possibility that three or more of the variables are collinear but no two taken alone display evidence of this cannot categorically be ruled out.

[21] While the absence of high R^2 values in conjunction with low t-statistic values for the regressions strongly suggests that multicollinearity is not a problem, further analysis involving the calculation of Variance Inflation factors was undertaken. The results of this analysis support the conclusion that multicollinearity is not a problem.

Table 4.4 Correlation between Independent Variables

	DFEM	DMARR	NDEP	AGE	EDU	INC	CINC	NASS
DFEM	1	-	-	-	-	-	-	-
DMARR	0.0502	1	-	-	-	-	-	-
NDEP	-0.2054	**0.3576**	1	-	-	-	-	-
AGE	-0.0552	0.2771	-0.0213	1	-	-	-	-
EDU	-0.1097	-0.0602	0.0751	-0.2556	1	-	-	-
INC	**-0.3210**	0.1229	0.2739	-0.0772	**0.3358**	1	-	-
CINC	-0.1127	**0.3461**	0.2609	-0.0770	0.2981	**0.7940**	1	-
NASS	-0.1032	**0.3627**	0.2017	**0.5422**	-0.0030	**0.3433**	**0.4012**	1

DFEM is a dummy variable taking the value of unity if the respondent is female and zero for males. DMARR is a dummy variable taking the value of unity if the respondent is married and zero if unmarried. NDEP is a variable measuring the number of family dependents. AGE is the respondent's age in years. Ordered categorical variables for education (EDU); income (INC); combined income (CINC) and net assets (NASS) as defined in Table 4.2.

Model (4.1) can easily be modified to consider a range of special cases, for example:

The general model for males is (i.e. DFEM = 0):

$$\begin{aligned} RTS = {} & \alpha_0 + \alpha_2 DMARR + \alpha_3 NDEP + \alpha_4 AGE + \alpha_5 EDU \\ & + \alpha_6 INC + \alpha_7 (DMARR * CINC) + \alpha_8 NASS + \varepsilon \end{aligned} \tag{4.1a}$$

The general model for females is (i.e. DFEM = 1):

$$\begin{aligned} RTS = {} & \alpha_0 + \alpha_1 + \alpha_2 DMARR + \alpha_3 NDEP + \alpha_4 AGE + \alpha_5 EDU \\ & + \alpha_6 INC + \alpha_7 (DMARR * CINC) + \alpha_8 NASS + \varepsilon \end{aligned} \tag{4.1b}$$

The model for married males is (i.e. DFEM = 0 and DMARR = 1):

$$\begin{aligned} RTS = {} & \alpha_0 + \alpha_2 + \alpha_3 NDEP + \alpha_4 AGE + \alpha_5 EDU \\ & + \alpha_6 INC + \alpha_7 CINC + \alpha_8 NASS + \varepsilon \end{aligned} \tag{4.1c}$$

The model for unmarried males is (i.e. DFEM = 0 and DMARR = 0):

$$RTS = \alpha_0 + \alpha_3 NDEP + \alpha_4 AGE + \alpha_5 EDU + \alpha_6 INC + \alpha_8 NASS + \varepsilon \tag{4.1d}$$

The model for married females is (i.e. DFEM = 1 and DMARR = 1):

$$\begin{aligned} RTS = {} & \alpha_0 + \alpha_1 + \alpha_2 + \alpha_3 NDEP + \alpha_4 AGE + \alpha_5 EDU \\ & + \alpha_6 INC + \alpha_7 CINC + \alpha_8 NASS + \varepsilon \end{aligned} \tag{4.1e}$$

The model for unmarried females is (i.e. DFEM = 1 and DMARR = 0):

$$\begin{aligned} RTS = {} & \alpha_0 + \alpha_1 + \alpha_3 NDEP + \alpha_4 AGE + \alpha_5 EDU \\ & + \alpha_6 INC + \alpha_8 NASS + \varepsilon \end{aligned} \tag{4.1f}$$

4.5. Basic Regression Results

Estimation results for the model specified in equation (4.1) are reported in Table 4.5. All of the demographic characteristics tested in equation (4.1) were found to be significant at the 1% level for our sample group. The constant term in this model, 65.79, represents a baseline risk tolerance score which will be adjusted up or down according to the characteristics of the individual respondent. The coefficients for the independent variables indicate the direction and magnitude of the effect on risk tolerance. For example, gender is the most significant of the specified determinants of risk tolerance and a female will exhibit a RTS 5.87 points less than a demographically equivalent male. Marriage is also an important determinant, reducing the RTS by 2.29 points. The results also support the view held by many in the investment industry that investors become more risk averse with age: the RTS decreases by 3.24 points for each decade of birthdays.

Table 4.5 Basic Aggregate Regression Results

Variable	Coefficient	Std. error	t-statistic	p-value
Constant	65.794**	0.587	112.06	0.000
DFEM	-5.8687**	0.210	-28.01	0.000
DMARR	-2.2940**	0.511	-4.49	0.000
NDEP	-0.1989**	0.073	-2.73	0.006
AGE	-0.3240**	0.009	-34.74	0.000
EDU	1.0997**	0.103	10.73	0.000
INC	1.7050**	0.120	14.21	0.000
DMARR*CINC	0.5855**	0.137	4.28	0.000
NASS	0.8651**	0.105	8.23	0.000
Adjusted R-squared	= 0.242			
Number of observations	= 15,916			

This table reports regression results in which the dependent variable is the respondent's risk tolerance score (created by FinaMetrica) and the independent variables are: DFEM, a dummy variable taking the value of unity if the respondent is female and zero for males; DMARR, a dummy variable taking the value of unity if the respondent is married and zero if unmarried; NDEP, a variable measuring the number of family dependents; AGE, the respondent's age in years; EDU, an ordered categorical variable measuring education level; INC, an ordered categorical variable measuring income; DMARR*CINC, an interactive variable created by the product of DMARR and CINC, where CINC is an ordered categorical variable measuring combined income and NASS, an ordered categorical variable measuring net assets. The ordered categorical variables for education (EDU); income (INC); combined income (CINC) and net assets (NASS) are defined in Table 4.2. White Heteroskedasticity-Consistent Standard Errors and Covariance are used.
* Significant at the 5% level
** Significant at the 1% level

On the other hand, RTS is positively related to both income and education, with the former increasing the RTS by 1.70 points per category (as defined in Table 4.2) and the latter by 1.10 points per category. Risk tolerance is also positively related to the respondent's net assets, although this variable has less influence than income and education per category: the RTS increases 0.87 points per category. The interactive variable, DMARR*CINC, captures the impact of the combined income effect associated with marriage (or defacto relationships) and shows that RTS increases by 0.59 points per combined income category.

Overall, the results, based on the responses of a large-sample of investors, indicate that all of the demographic characteristics are significant in explaining financial risk tolerance. From a statistical significance point of view it seems that the most influential demographics are: Age, Gender, Education and Income.

4.6. Exploring the Role of Gender

Good reason exists to believe that males and females behave differently with regard to risk tolerance and this can be explored further in the context of model (4.1) by extending it into the following dummy variable enhanced regression specification:

$$\begin{aligned} RTS = {} & \delta_0 + \delta_1 DMARR + \delta_2 NDEP + \delta_3 AGE + \delta_4 EDU + \delta_5 INC + \delta_6 (DMARR * CINC) + \delta_7 NASS \\ & + \delta_{0\Delta} DFEM + \delta_{1\Delta} DFEM * DMARR + \delta_{2\Delta} DFEM * NDEP + \delta_{3\Delta} DFEM * AGE \\ & + \delta_{4\Delta} DFEM * EDU + \delta_{5\Delta} DFEM * INC + \delta_{6\Delta} DFEM * (DMARR * CINC) \\ & + \delta_{7\Delta} DFEM * NASS + \varepsilon \end{aligned} \tag{4.2}$$

In this form the model can test the increment in each coefficient derived from being female relative to the base case of being male, and thereby provide deeper insight into the impact of gender on risk tolerance.

Model (4.2) can be easily converted into a range of special cases, for example:

The general model for males is (i.e. DFEM = 0):

$$RTS = \delta_0 + \delta_1 DMARR + \delta_2 NDEP + \delta_3 AGE + \delta_4 EDU + \delta_5 INC + \delta_6 (DMARR * CINC) + \delta_7 NASS + \varepsilon \tag{4.2a}$$

The general model for females is (i.e. DFEM = 1):

$$RTS = \delta_0 + \delta_{0\Delta} + (\delta_1 + \delta_{1\Delta})DMARR + (\delta_2 + \delta_{2\Delta})NDEP + (\delta_3 + \delta_{3\Delta})AGE + (\delta_4 + \delta_{4\Delta})EDU$$
$$+ (\delta_5 + \delta_{5\Delta})INC + (\delta_6 + \delta_{6\Delta})(DMARR * CINC) + (\delta_7 + \delta_{7\Delta})NASS + \varepsilon \quad (4.2b)$$

Estimation results for the model specified in equation (4.2) are reported in Table 4.6. Table 4.6 is partitioned with the upper panel showing a baseline case for males and the lower panel showing the incremental effect of gender. In other words, the lower panel shows the incremental effect for each coefficient of being female relative to the base case of being male, and thereby identifies those characteristics that are differentially important for females.

Table 4.6 Dummy Variable Regression Results – Conditioned on Gender

Variable	Coefficient	Std. error	t-statistic	p-value
Constant	67.304**	0.733	91.77	0.000
DMARR	-3.6307**	0.730	-4.98	0.000
NDEP	-0.2876**	0.088	-3.27	0.001
AGE	-0.3390**	0.012	-28.31	0.000
EDU	1.0883**	0.131	8.30	0.000
INC	1.2486**	0.176	7.09	0.000
DMARR*CINC	1.0236**	0.200	5.12	0.000
NASS	1.0374**	0.133	7.78	0.000
DFEM	-9.6019**	1.178	-8.15	0.000
DFEM*DMARR	2.6589*	1.030	2.58	0.010
DFEM*NDEP	0.4096*	0.163	2.52	0.012
DFEM*AGE	0.0485*	0.019	2.49	0.013
DFEM*EDU	0.0515	0.212	0.24	0.808
DFEM*INC	0.9786**	0.251	3.89	0.000
DFEM*DMARR*CINC	-0.7822**	0.279	-2.81	0.005
DFEM*NASS	-0.4823*	0.218	-2.22	0.027

Adjusted R-squared = 0.244
Number of observations = 15,916

This table reports regression results in which the dependent variable is respondent's risk tolerance score (created by FinaMetrica) and the independent variables are combinations of: DFEM, a dummy variable taking the value of unity if the respondent is female and zero for males; DMARR, a dummy variable taking the value of unity if the respondent is married and zero if unmarried; NDEP, a variable measuring the number of family dependents; AGE, the respondent's age in years. Ordered categorical variables for education (EDU); income (INC); combined income (CINC) and net assets (NASS) are defined in Table 4.2. White Heteroskedasticity-Consistent Standard Errors and Covariance are used.
* Significant at the 5% level
** Significant at the 1% level

First, it is noticed that the fixed (constant) component of RTS is lower for females by 9.6 points. However, the magnitude of this impact is generally tempered once the other demographic characteristics are taken into account. Most noticeably, marriage is a differentially important characteristic, having a less negative impact on risk tolerance for females than the negative impact found for males. That is, for males, being married reduces RTS by 3.63 points, whereas for females, being married reduces RTS by about 1 point (i.e. 3.63- 2.66). Similarly, the number of dependents is positively related to risk tolerance for females but negatively related for males, although in each case the magnitude of the impact is relatively small. Interestingly, while age reduces risk tolerance by 3.39 points per decade for males, its differential impact for females is positive but negligible, being associated with a decrease of 2.91 points per decade (i.e. 0.48 points lower in magnitude).

On the other hand, the combined income effect derived from marriage and the level of net assets of the respondent, which have a positive impacts of 1.02 and 1.03 points per category respectively for males, have correspondingly incremental negative impacts of –0.78 and –0.48 points for females.

Education was not found to be a significant differentiating variable in explaining the RTS of females. While important for both males and females in the sense that it is associated with an increase by 1.09 points per education category, the results show that no more or less importance is attached to it by females.

As an example, a 40 year old, university educated, married female with one dependent, earning $50,000 - $100,000, a combined income of $100,000 - $200,000 and net assets of

\$150,000 - \$500,000 would have a risk tolerance of: 59.1.[22] This compares to the demographically equivalent male with a risk tolerance of 65.1.

The combined model reported in Table 4.5 somewhat obscures the direct effects of the demographic variables on female RTS. Accordingly, as noted above, the general model for evaluating the determinants of RTS [equation (4.1)] can be converted to a general model for females [Equation (4.1b)]:

$$\begin{aligned} RTS = {} & \alpha_0 + \alpha_1 + \alpha_2 DMARR + \alpha_3 NDEP + \alpha_4 AGE + \alpha_5 EDU \\ & + \alpha_6 INC + \alpha_7 (DMARR * CINC) + \alpha_8 NASS + \varepsilon \end{aligned} \qquad (4.1b)$$

Section 4.6 reported the basic regression results for the general model and established that all the demographic characteristics were important determinants of an individual's attitude to risk. When the general model for females was tested on the data, it was found that the respondent's age, education, income and net assets were the most important determinants of risk tolerance. To investigate further the influence of these factors on the RTS, a parsimonious version of equation (4.1b) may be estimated in which only the most important components of equation (4.1b) are retained. The parsimonious model that focuses on these determinants may be specified as:

$$RTS = \chi_0 + \chi_1 AGE + \chi_2 EDU + \chi_3 INC + \chi_4 NASS + \varepsilon \qquad (4.3)$$

The estimated output for equation 4.3 is presented in Table 4.7. All of the estimated coefficients are significant at the 1% level. Here the constant term of 57.59 represents the

[22] This is calculated as: 67.304 + (- 9.6019) + (-3.6307 + 2.6589) + (-0.2876 + 0.4096) + (40*-0.3390 + 40*0.0485) + (4*1.0883 +4*0.0515) + (3*1.2486+ 3*0.9786) + (4*1.0236 + 4*-0.7822) + (3*1.0374 + 3*-0.4823) = 59.10

baseline for females. The impact of the respondent's age, education, income and net assets can be estimated by examining the sign and magnitude of the estimated coefficients for these variables. For example, we can see that a female's RTS declines by 2.98 points with each passing decade but increased levels of education, income and net assets (as defined by the categories in Table 4.2) will increase her RTS by 1.16, 2.30 and 0.62 points per category, respectively.

Table 4.7 Parsimonious Model for Female Respondents

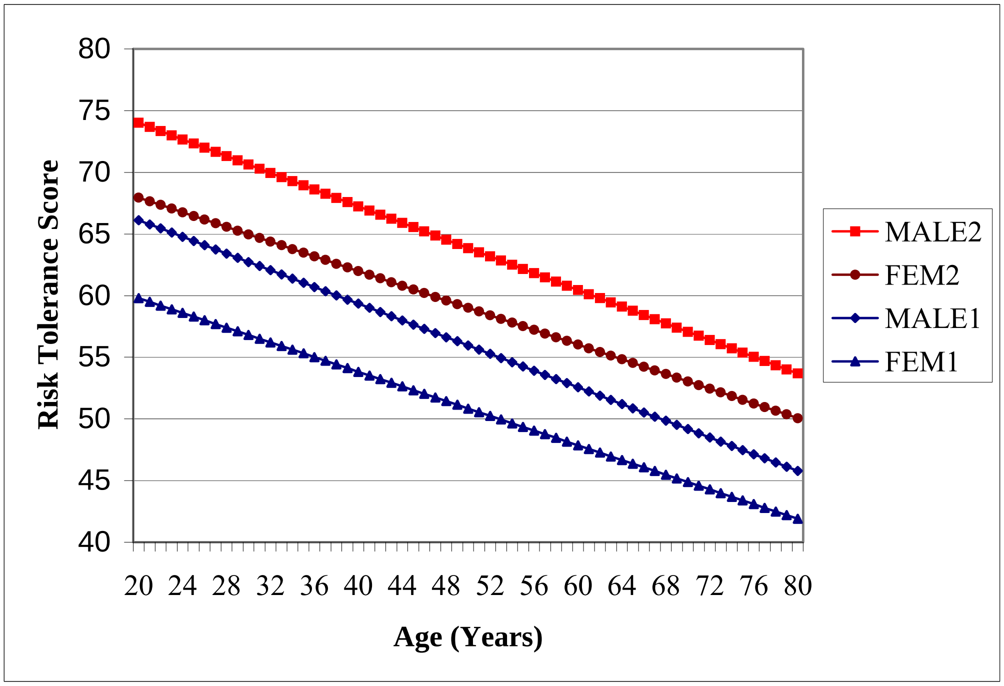
Variable	Coefficient	Std. error	t-statistic	p-value
Constant	57.588**	0.881	65.37	0.000
AGE	-0.2982**	0.014	-20.78	0.000
EDU	1.1591**	0.164	7.05	0.000
INC	2.2987**	0.167	13.78	0.000
NASS	0.6240**	0.156	4.01	0.000
Adjusted R-squared	= 0.187			
Number of observations	= 5,323			

This table reports regression results in which the dependent variable is respondent's risk tolerance score (created by FinaMetrica) and the independent variables are: AGE, the respondent's age in years. Ordered categorical variables for education (EDU); income (INC); and net assets (NASS) are defined in Table 4.2. White Heteroskedasticity-Consistent Standard Errors and Covariance are used.
* Significant at the 5% level ** Significant at the 1% level

Figures 4.2 and 4.3 illustrate some cases that are derived from the results reported in Tables 4.6 and 4.7.[23] In Figure 4.2 we have chosen male and female examples from each end of the socio-economic spectrum to observe how the risk tolerance score varies with age. In each case the negative and monotonic relationship between age and risk tolerance can be clearly seen and the impact of socio-economic factors is readily apparent.

[23] The top panel of Table 4.6 represents the parsimonious model for males and Table 4.7 the comparable model for females.

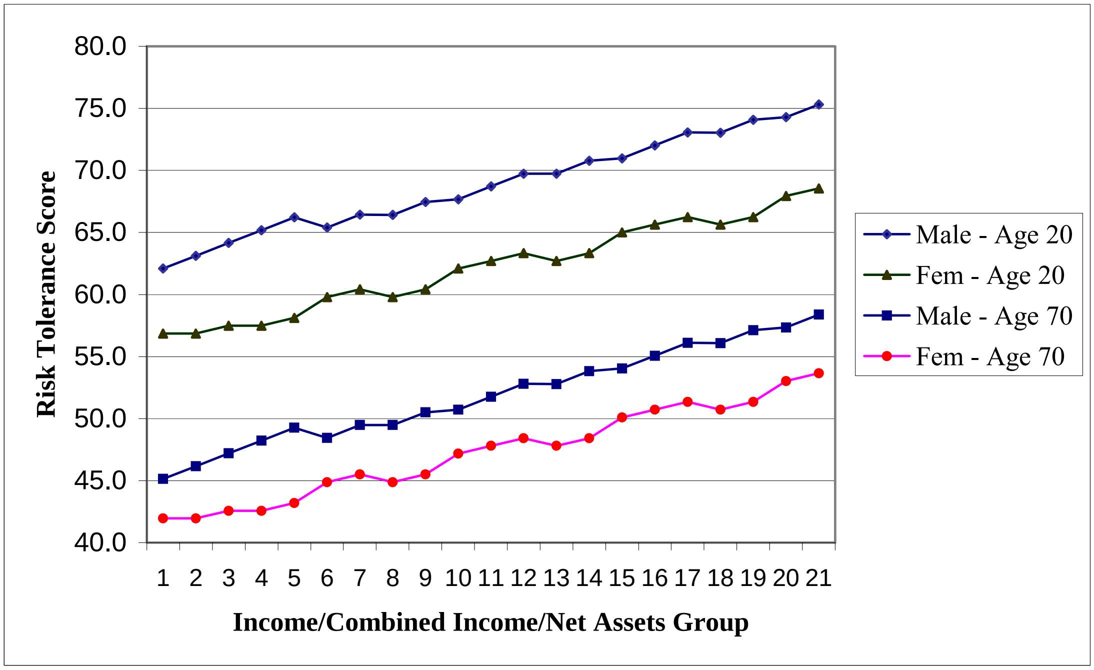
Figure 4.2 Predicted RTS from Basic Parsimonious Male/Female Models



Note: This Figure displays four illustrative cases from the regression equations estimated for Tables 4.6 and 4.7. All cases represent unmarried respondents. 'FEM1' and 'MALE1' represent a female and male pair that habitate the lower end of the socio-economic spectrum. Specifically, 'FEM1' represents female respondents who have any number of family dependents; have completed a high school education only; have an income in the range $30,000 - $50,000; and have net assets in the range $50,000 - $150,000. 'MALE1' represents male respondents who have four family dependents; have completed a high school education only; have an income in the range $30,000 - $50,000; and have net assets in the range $50,000 - $150,000. In contrast, 'FEM2' and 'MALE2' represent a female and male pair that habitate the upper end of the socio-economic spectrum. Specifically, 'FEM2' represents female respondents who have any number of family dependents; have university qualifications; have an income in the range $100,000 - $200,000; and have net assets in the range $500,000 - $1,000,000. 'MALE2' represents male respondents who have no family dependents; have university qualifications; have an income in the range $100,000 - $200,000; and have net assets in the range $500,000 - $1,000,000.

In Figure 4.3 a young (20 year old) male and a matching young female and an elderly (70 year old) male and a matching elderly female, each with high school education, have been selected to illustrate how the risk tolerance score varies with changes in the income and wealth positions for each. Age and gender differences are clearly evident and are maintained as income and wealth increase.

Figure 4.3 Predicted RTS from Basic Parsimonious Male/Female Models across Income/Combined Income/Net Assets Groups



Note: This Figure displays four illustrative cases from the regression equation estimated for Tables 4.6 and 4.7. All four cases are based on (a) one dependent family member; and (b) high school as the highest educational qualification. Males are married, whereas females may be married or unmarried. The Income / Combined Income / Net Asset groups are defined as follows:

I/CI/NA Group	Income	Combined Income	Net Assets
1	< $30,000	< $30,000	< $50,000
2	< $30,000	$30,000 - $50,000	< $50,000
3	< $30,000	$30,000 - $50,000	$50,000 - $150,000
4	< $30,000	$50,000 - $100,000	$50,000 - $150,000
5	< $30,000	$50,000 - $100,000	$150,000 - $500,000
6	$30,000 - $50,000	$30,000 - $50,000	$50,000 - $150,000
7	$30,000 - $50,000	$30,000 - $50,000	$150,000 - $500,000
8	$30,000 - $50,000	$50,000 - $100,000	$50,000 - $150,000
9	$30,000 - $50,000	$50,000 - $100,000	$150,000 - $500,000
10	$50,000 - $100,000	$50,000 - $100,000	$50,000 - $150,000
11	$50,000 - $100,000	$50,000 - $100,000	$150,000 - $500,000
12	$50,000 - $100,000	$50,000 - $100,000	$500,000 - $1,000,000
13	$50,000 - $100,000	$100,000 - $200,000	$150,000 - $500,000
14	$50,000 - $100,000	$100,000 - $200,000	$500,000 - $1,000,000
15	$100,000 - $200,000	$100,000 - $200,000	$150,000 - $500,000
16	$100,000 - $200,000	$100,000 - $200,000	$500,000 - $1,000,000
17	$100,000 - $200,000	$100,000 - $200,000	> $1,000,000
18	$100,000 - $200,000	> $200,000	$500,000 - $1,000,000
19	$100,000 - $200,000	> $200,000	> $1,000,000
20	> $200,000	> $200,000	$500,000 - $1,000,000
21	> $200,000	> $200,000	> $1,000,000

4.7. The Presence of Non-linearities in the Model

Consistent with the research presented in Chapters 2 and 3, an interesting extension of the research in this chapter is to test the robustness of the linearity assumption implicit in the specification of the model. Indeed, while Chapters 2 and 3 picked up on previous research by Riley and Chow (1992) and Bajtelsmit and VanDerhai (1997) that pointed to non-linearities in the relationship between age and risk tolerance, non-linearities are plausible also for the following variables: NDEP; INC; CINC and NASS.[24] Once again, a simple test for the presence of non-linearities is to introduce quadratic versions of the independent variables. Accordingly, the non-linear model takes the form:

$$RTS = \gamma_0 + \gamma_1 DFEM + \gamma_2 DMARR + \gamma_3 NDEP + \gamma_4 NDEP^2 + \gamma_5 AGE + \gamma_6 AGE^2 + \gamma_7 EDU \\ + \gamma_8 INC + \gamma_9 INC^2 + \gamma_{10} DMARR * CINC + \gamma_{11} DMARR * CINC^2 + \gamma_{12} NASS + \varepsilon \tag{4.4}$$

Table 4.8 Non-Linear Regression Results

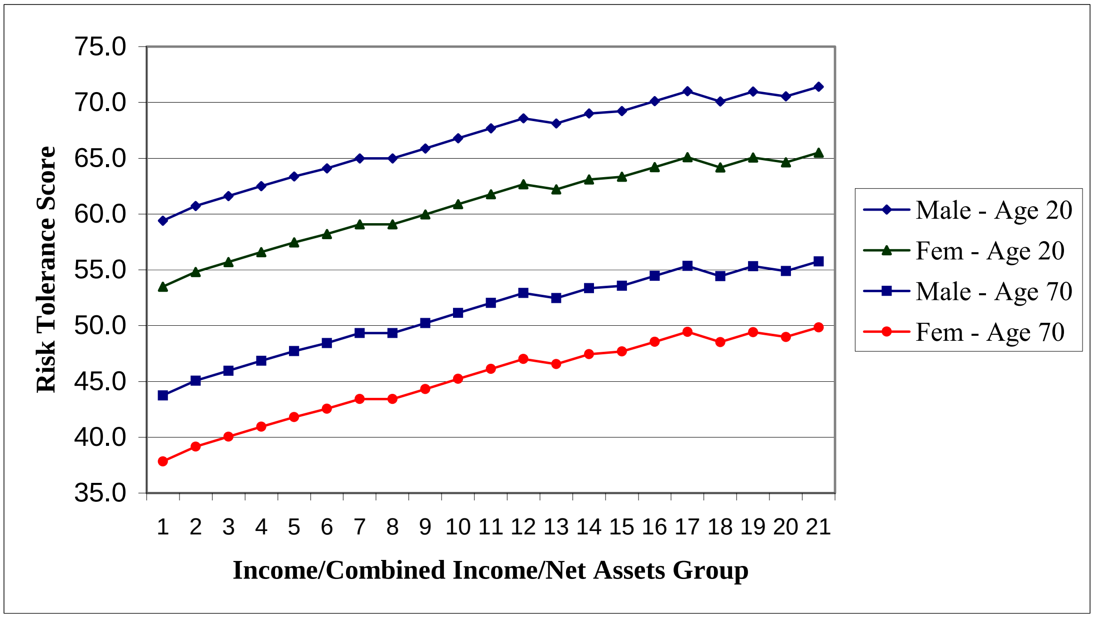
Variable	Coefficient	Std. error	t-statistic	P-value
Constant	59.192**	1.191	49.70	0.000
DFEM	-5.9086**	0.212	-27.93	0.000
DMARR	-4.4117**	0.852	-5.18	0.000
NDEP	-0.6373**	0.188	-3.38	0.001
$NDEP^2$	0.0893*	0.042	2.12	0.034
AGE	-0.0964	0.052	-1.86	0.063
AGE^2	-0.0024**	0.001	-4.40	0.000
EDU	1.1006**	0.103	10.68	0.000
INC	3.5264**	0.413	8.53	0.000
INC^2	-0.3430**	0.076	-4.54	0.000
DMARR*CINC	2.0101**	0.538	3.74	0.000
$DMARR*CINC^2$	-0.2260**	0.087	-2.61	0.009
NASS	0.8837**	0.106	8.32	0.000
Adjusted R-squared	= 0.247			
Number of observations	15,916			

This table reports regression results in which the dependent variable is respondent's risk tolerance score (created by FinaMetrica) and the independent variables involve linear and/or quadratic versions of: DFEM, a dummy variable taking the value of unity if the respondent is female and zero for males; DMARR, a dummy variable taking the value of unity if the respondent is married and zero if unmarried; NDEP, a variable measuring the number of family dependents; AGE, the respondent's age in years. Ordered categorical variables for education (EDU); income (INC); combined income (CINC) and net assets (NASS) are defined in Table 4.2. White Heteroskedasticity-Consistent Standard Errors & Covariance are used.
* Significant at the 5% level ** Significant at the 1% level

[24] The non-linear effect in NASS is dropped due to insignificant results.

The estimated regression results are presented in Table 4.8. The significance of all of the estimated coefficients provides clear evidence of nonlinear effects in the relationship between RTS and NDEP, AGE, INC and CINC. Specifically, it can be seen that RTS decreasing at a decreasing rate as the number of dependents increases and decreasing at an increasing rate as reported age increases. On the other hand, RTS increases at a decreasing rate as income and combined income increase. A more insightful impression of this nonlinearity may be obtained using the estimated coefficients of the parsimonious model specified in equation (4.4) and plotting the predicted RTS for a collection of characterized cases. Figure 4.4 presents a plot of the predicted RTS for a young (20 year old) male and a similar female and an elderly (70 year old) male and a similar female who, in each case, are married, have one dependent family member and have completed high school. Similar to the counterpart plots given in Figure 4.3, age and gender differences are clearly evident and are maintained as income and wealth increase. Compared to Figure 4.3, the non-linear model provides lower RTS estimates on a case by case basis, suggesting that ignoring non-linearities may induce overestimation of RTS (at least for these types of individuals).

Figure 4.4 Predicted RTS from Non-Linear Model across Income/Combined Income/Net Asset Groups



Note: This Figure displays four illustrative cases from the regression equation estimated for Table 4.8. All four cases are based on (a) a married respondent; (b) one dependent family member; and (c) high school as the highest educational qualification. The Income / Combined Income / Net Asset groups are defined as follows:

I/CI/NA Group	Income	Combined Income	Net Assets
1	< $30,000	< $30,000	< $50,000
2	< $30,000	$30,000 - $50,000	< $50,000
3	< $30,000	$30,000 - $50,000	$50,000 - $150,000
4	< $30,000	$50,000 - $100,000	$50,000 - $150,000
5	< $30,000	$50,000 - $100,000	$150,000 - $500,000
6	$30,000 - $50,000	$30,000 - $50,000	$50,000 - $150,000
7	$30,000 - $50,000	$30,000 - $50,000	$150,000 - $500,000
8	$30,000 - $50,000	$50,000 - $100,000	$50,000 - $150,000
9	$30,000 - $50,000	$50,000 - $100,000	$150,000 - $500,000
10	$50,000 - $100,000	$50,000 - $100,000	$50,000 - $150,000
11	$50,000 - $100,000	$50,000 - $100,000	$150,000 - $500,000
12	$50,000 - $100,000	$50,000 - $100,000	$500,000 - $1,000,000
13	$50,000 - $100,000	$100,000 - $200,000	$150,000 - $500,000
14	$50,000 - $100,000	$100,000 - $200,000	$500,000 - $1,000,000
15	$100,000 - $200,000	$100,000 - $200,000	$150,000 - $500,000
16	$100,000 - $200,000	$100,000 - $200,000	$500,000 - $1,000,000
17	$100,000 - $200,000	$100,000 - $200,000	> $1,000,000
18	$100,000 - $200,000	> $200,000	$500,000 - $1,000,000
19	$100,000 - $200,000	> $200,000	> $1,000,000
20	> $200,000	> $200,000	$500,000 - $1,000,000
21	> $200,000	> $200,000	> $1,000,000

4.8. Conclusion

Attitudes towards risk and their impact on asset allocation decisions will be an important determinant of financial well-being in retirement. This analysis, of a very large database of psychometrically-derived risk profiles of Australians aged between 20 and 80 years, provides evidence that women differ from men in their attitude to financial risk taking. The examination of a large Australian database also provides a response to the observation made by Jiankoplos and Bernasek (1998) that most of the risk tolerance research uses United States data and consequently the results could be country specific.

Regression analysis of risk tolerance scores (RTS) on the demographic characteristics of gender, marital status, number of dependents, age, education, income, combined income and net assets revealed each of these characteristics to be significant at the 1% level, with the first four characteristics having a negative relationship with RTS. The impact of gender was explored through dummy variable enhanced regression analysis constructed to test the increment in each demographic coefficient derived from being female relative to the base case of being male. While it was found that the fixed component of the RTS was 9.6 points lower for females, the magnitude of this impact is reduced once the other demographic characteristics are taken into account. Marriage and number of dependents were found to be differentially important characteristics, with marriage having a less negative impact on risk tolerance for females than the negative impact found for males. Age reduces risk tolerance by 3.39 points per decade for males, and its differential impact for females is positive but negligible, being associated with a decrease of 2.91 points per decade (i.e. 0.48 points lower in magnitude).

On the other hand, the combined income effect derived from marriage and the level of net assets of the respondent, which have positive impacts per category for males, have correspondingly incremental negative impacts for females. Education was not found to be a significant differentiating variable in explaining the RTS of females. While important for both males and females in the sense that it is associated with an increase in RTS per education category, the results show that no more or less importance is attached to it by females. Finally, the research revealed evidence of nonlinear effects in the relationship between RTS and the number of dependents, age and income and combined income.

In the context of an aging and increasingly female world, the key implications of this research are most apparent in the managed funds industry over a medium to longer term timeframe (looking at 2030 and beyond). As the baby boomer bulge moves through the age profile, the gender composition will shift further in favor of women. The extent to which women do have more conservative risk profiles and the extent to which this conservatism is exacerbated with age, we expect to see asset allocation decisions leading to an overall shift to less risky investment portfolios. Importantly, the existence of a positive equity premium means that such a shift in overall asset allocation has the potential to lead to lower levels of wealth for women in their retirement years. At a macro level, in the absence of countervailing forces at play, it may lead to lower levels of 'speculative' capital being available for venture capital and other extreme risk projects that currently attract funding.

Part B: Supply Side Studies

Chapter 5: An Examination of Australian Equity Trusts for Selectivity and Market Timing Performance[25]

5.1. Introduction

The issue of managed fund performance has been the subject of increased interest in both the academic and practitioner communities in recent years.[26] Given that the majority of fund managers classify themselves as either stock pickers or market timers, it is not surprising that a major focus of the literature on managed fund performance has been the identification and differentiation of security selection (microforecasting) skills and market timing (macroforecasting) skills on the part of investment managers. While changes in the composition of stocks in a portfolio can impact on the fund's systematic risk, it is the latter activity which is more likely to have the greatest impact on the fund's systematic risk.

It is in the area of macroforecasting, namely the identification of market timing ability, in which the current chapter focuses its attention. Here the logic of the analysis is to establish a relationship between the systematic risk of a fund and market timing ability on the part of a fund manager. Timing ability is usually summarised as a decision by a manager to be in or out of the equity market, where being out of the (higher risk) equity market implies being in the (lower risk) fixed income market. As a result of fund managers effecting changes in the risk level of the portfolio, the relationship between portfolio returns and market returns will be non-linear. Studies generally have attempted to accommodate this non-linearity and identify changes in the systematic risk of funds through the use of some form of quadratic regression technique (Treynor and Mazuy, 1966, Admati, Bhattacharya, Pfleiderer and Ross, 1986), or

[25] Parts of this chapter are drawn from a paper published by the candidate: Hallahan, T. and Faff, R (1999). An Examination of Australian Equity Trusts for Selectivity and Market Timing Performance, *Journal of Multinational Financial Management*, 9, 387-402.

[26] Surveys conducted by Lakonishok, Shleifer and Vishny (1992), Ippolito (1993) and Shukla and Trzcinka (1994) document the renewed interest in portfolio performance and provide an overview of the themes which have emerged in the literature.

the application of a 'dual beta' specification (Henriksson and Merton, 1981, Jagannathan and Korajczyk, 1986, Sinclair, 1990 and Fletcher, 1995).

The pioneering work of Treynor and Mazuy (1966) recognised that active market timing by a fund manager would induce nonstationarity of fund systematic risk. If successful, market timing would result in curvature of the fund's characteristic line, and it was suggested that this non-linearity could be captured by including a quadratic term in the regression used to estimate Jensen's Alpha. The appeal of the Treynor and Mazuy model lies in its simplicity: the alpha value identifies security selection skills and the coefficient on the quadratic term measures market timing ability. Their test of the model on a sample of 57 mutual funds found that only one of the funds displayed significant timing ability.

Subsequent studies of fund managers' macroforecasting skills have either refined the Treynor and Mazuy quadratic regression approach by, for example, incorporating time-varying betas Chen and Stockum (1986) or conditioning on public information variables Ferson and Schadt (1996), or have invoked an alternative definition of market timing ability Hendrickson and Merton (1981). An interesting feature of the literature is the number of studies (for example, Kon, 1983, Chang and Lewellen, 1984, Henriksson, 1984, Grinblatt and Titman, 1989, Lehmann and Modest, 1987, Cumby and Glen, 1990, Connor and Korajczyk, 1991, Coggin and Hunter, 1993) which report negative market timing skills and a negative relationship between selectivity and timing. However, Lee and Rahman (1990) found that 28 of the 93 funds in their sample exhibited significantly positive timing ability. This figure reduced to 16 funds when the regression estimates were adjusted for heteroscedasticity.

Fletcher (1995) conducted a study of the selectivity and market timing performance of a sample of UK unit trusts over the ten-year period 1980 to 1989. He applied an approach that assessed market timing performance using two different empirical specifications. First, a quadratic market model framework was used following the work of Chen and Stockum (1986). Second, the Henriksson and Merton (1981) 'dual-beta' market model was also applied. In general, he found, like Sinclair (1990), that the funds tended to exhibit 'perverse' market timing performance but that this seemed to be typically offset by superior security selection ability. As observed by Fletcher (1995) this apparent trade-off between selectivity and market timing is consistent with existing US evidence – for example, Henriksson (1984); Connor and Korajcyzk (1991); and Coggin, Fabozzi and Rahman (1993). An explanation of this phenomenon is yet to be found. [27]

Bello and Janjigian (1997) extended the Treynor and Mazuy model to incorporate two additional indices to take account of the inclusion of non-S&P 500 stocks in mutual fund portfolios. The data set comprised 633 funds classified by investment objective as either aggressive, small company, growth, equity-income or balanced. Comparing the extended model to the standard Treynor and Mazuy model, it was found that where the former indicated superior selectivity only for the growth and equity-income categories, the latter found superior selectivity across all categories. With regard to timing, the former model showed negative timing which was significant for all but the balanced category, whereas the extended model found evidence of significant positive timing for the aggressive, small company and growth funds and negative timing in the other categories. These results call into question earlier findings which suggested timing skills were predominantly negative and negatively correlated with selectivity skills.

Whilst much of the evidence indicates that fund managers possess perverse market timing ability, studies by Ferson and Schadt (1996) and Kothari and Warner (2001) suggest that the

[27] See Fletcher (1995, pp. 153-4) for a good discussion of the possible reasons for the trade-off between selectivity and timing, explored in the literature.

models commonly used to measure market timing ability are misspecified, and that this misspecification may explain the reported results.

The investigation of fund market timing performance using Australian data is an area of very limited research activity. Sinclair (1990) provided the first published Australian evidence on the market timing issue. His study involved a sample of sixteen pooled superannuation funds over the seven-year period 1981 to 1987. He applied an approach that combined two empirical strategies. First, to try and identify shifts in fund risk, the Brown, Durbin and Evans (1975) and Quandt (1958, 1960) techniques were applied. Second, the market timing evidence was directly assessed in terms of the Henriksson and Merton (1981) 'dual-beta' market model. In general, he found that the funds tended to exhibit 'perverse' market timing performance. However, this seemed to be typically offset by superior security selection ability.

The principal issue to be examined in this chapter therefore is the market timing ability of a segment of the Australian investment fund industry, namely, Australian equity trusts. Following others in the literature (for example, Clare, Priestly and Thomas, 1998), this study takes on board the arguments of Leamer (1983) and Lo and MacKinlay (1990) who question the appropriateness of continued testing of an hypothesis using data from which the hypothesis was developed originally. Most of the previous studies of market timing use US mutual fund data. This study therefore extends the market timing literature by examining data from an alternative major capital market and by providing evidence on a more extensive Australian dataset than has been previously published. The approach followed involves running both quadratic excess returns market model and dual-beta excess returns market model regressions. In addition, some specification tests suggested by Jagannathan and Korajczyk (1986) are also applied.

The remainder of the chapter is structured as follows. Section 5.2 outlines the methodology. Section 5.3 discusses the data set used in the study. Section 5.4 presents the results of the empirical analysis, while Section 5.5 provides a summary and conclusions.

5.2. Empirical Framework

5.2.1. Basic Excess Returns Market Model

The starting point for analysis in this paper is the standard excess returns market model:

$$r_{it} = \alpha_i + \beta_i r_{mt} + e_{it} \tag{5.1}$$

where

- r_{it} is the excess return (the raw return less the risk-free rate) on fund i in month t;
- α_i is a measure of the abnormal performance of fund i;
- β_i is a measure the market beta risk for fund i;
- r_{mt} is the excess return on a benchmark market index; and
- e_{it} is a mean zero error term.

This model assumes that funds have no market timing ability. This specification can be altered to allow for market timing ability in two different ways. Following Fletcher (1995), this study utilises (a) the quadratic market model approach of Chen and Stockum (1986) and (b) the dual-beta market model specification of Henriksson and Merton (1981).

5.2.2. Quadratic Market Model

The quadratic version of the excess market model of Chen and Stockum (1986) takes the following form:

$$r_{it} = \alpha_i + \beta_i r_{mt} + \gamma_i r_{mt}^2 + e_{it} \tag{5.2}$$

where

γ_i is a measure of the market timing ability and all other variables are defined as above.

The alpha in equation (5.2) is a measure of the fund's security selection ability, whereas the gamma is an indication of the fund's market timing ability. Specifically, a positive (negative) gamma is consistent with a superior (perverse) market timing. This can be most easily seen by isolating the implied time-varying market model beta from the quadratic market model:

$$\beta_{it} = \beta_i + \gamma_i \, r_{mt} \tag{5.3}$$

With a positive gamma value, there is a positive relationship between the time-varying beta and the excess return on the market index. Hence, market timing ability is reflected by a higher market exposure when excess market returns are higher and a lower market exposure when excess market returns are lower.

5.2.3. Dual-Beta Market Model

Alternatively, the dual-beta excess returns market model of Henriksson and Merton (1981) takes the form:

$$r_{it} = \alpha_i + \beta_{1i} \, r_{mt} + \beta_{2i} \, D \, r_{mt} + e_{it} \tag{5.4}$$

where

D is a dummy variable which takes a value of negative unity for months in which r_{mt} is negative and a value of zero otherwise and all other variables are defined as above.

The alpha in equation (5.4) is a measure of the fund's security selection ability, whereas the second beta term is an indication of the fund's market timing ability. Specifically, a positive β_{2i} is consistent with superior market timing performance.

5.2.4. Specification Tests

Jagannathan and Korajczyk (1986) suggested exclusion restrictions specification tests for these market timing models and they are applied in the current paper.[28] Specifically, the exclusion restriction test is one in which the market-timing model is augmented by additional variable(s) of a higher order. The additional variables should not have significant estimated coefficients if the market-timing model is appropriate. Such specification tests are applied to both of the market-timing models outlined above, following Jagannathan and Korajczyk (1986).

First, consider the quadratic market model which Jagannathan and Korajczyk (1986) augment by a cubic term.

$$r_{it} = \alpha_i + \beta_i r_{mt} + \gamma_i r_{mt}^2 + \delta_i r_{mt}^3 + e_{it} \tag{5.5}$$

Interestingly, this cubic market model is not merely an artificial empirical specification. Recently, Fang and Lai (1997) building on work by Scott and Horvath (1980) and others, devise and tested a four-moment (co-kurtosis) CAPM utilising this cubic market model framework. Hence, the extent to which we uncover a significant cubic term may reflect on the empirical applicability of the four-moment CAPM.

[28] They also suggest performing a White's (1980) test of linearity. Since all regressions in this study are estimated using the White (1980) heteroskedasticity adjustment, the associated linearity tests are not undertaken.

On the other hand consider the exclusion restriction test which Jagannathan and Korajczyk (1986) suggest for the dual-beta market model specification, namely, to augment the model with a quadratic term.

$$r_{it} = \alpha_i + \beta_{1i}\, r_{mt} + \beta_{2i}\, D\, r_{mt} + \gamma_i\, r_{mt}^2 + e_{it} \tag{5.6}$$

5.3. Data

The data were supplied by Morningstar[29], an independent research house that monitors the funds industry. The sample comprises Australian equity trusts with complete monthly returns over the period January 1988 to September 1997. This produces a total sample size of 65 trusts. Further, the sample consists of trusts classified as (a) Diversified Growth Equity Trusts (37); (b) Diversified Income Equity Trusts (8); (c) Property Equity Trusts (9); (d) Diversified Resources Equity Trusts (6); and (e) Other Equity Trusts (5). Whilst all the funds fall within the broad category of Equity Trusts, the classifications represent a range of investment objectives with differing attendant risk profiles.

The choice of this sample period, in particular, the fact that it is entirely post-1987 and hence doesn't include the 1987 crash, is also important relative to some of the studies (such as Sinclair, 1990 and Fletcher, 1995) which have examined market timing performance. Specifically, applying a quadratic market model specification over a time interval including such an outlier can have quite dramatic effects since the impact has the great potential to be substantially magnified by squaring effect. Consequently, the current study tries to overcome this problem by choosing a post-crash sample.

[29] At the time the research was undertaken, the data were supplied by FPG Research. Subsequently, the business and operations of FPG Research were acquired by Morningstar and the Morningstar name replaced FPG Research.

The index series reflects changes in the value of an investment in a fund over time, and is based on a notional $10,000 investment in the fund. Monthly index values are calculated by reference to the month-end exit price of the fund, which is net of management fees and assumes reinvestment of all cash and bonus unit distributions. The index series therefore gives representative returns which an actual investor may have achieved and measures the monthly performance of the fund.

Continuous monthly return data were calculated from the index series produced by FPG Research for each fund. The Reserve Bank three-month Treasury Bill rate was used as a proxy for the risk-free rate. As the Reserve Bank data was in the form of annualised monthly figures these were transformed into equivalent monthly figures. The return on the All Ordinaries Accumulation Index was used as a market return proxy.

5.4. Empirical Results

The empirical analysis begins with an assessment of the performance of our sample of Australian equity trusts using the standard excess returns market model framework. The results are presented in Table 5.1. First consider the estimates of beta risk across our sample. It can be seen that in all cases except one, the trust betas are significantly different from zero at the 5 % level. The single exception is Advance Properties Securities Fund (FPG 905) from the property trust group. Indeed, property trusts as a group are typified by their low beta risk compared to the rest of our sample. The estimated property trust betas mostly fall in the range 0.07 to 0.4 and in all cases are significantly less than unity. This group of trusts provides the lowest beta risk case for our full sample - AMP Property Securities Trust (FPG 907), with a beta estimate of 0.0747.

Table 5.1 Excess Returns Market Model Performance of Australian Equity Trusts

Panel A: Diversified Growth Equity Trusts

	FPG Code	Alpha	Beta	Phi (AR(1))[a]	R-squared	D-W
1	22	-0.0003	0.5856**	-	0.489	2.082
		(-0.12)	(12.54)[b]			
2	74	-0.0025	0.8306**	-	0.249	2.657
		(-0.44)	(6.37)			
3	76	-0.0059	0.7194**	0.1650**	0.137	1.995
		(-0.68)	(4.53)	(1.97)		
4	77	-0.0040	0.7645**	-	0.337	2.459
		(-0.96)	(6.49)			
5	82	-0.0017	0.8258**	-0.3262**	0.696	2.041
		(-0.98)	(12.58)	(-2.64)		
6	120	0.0008	0.9547**	-0.2173**	0.928	2.044
		(0.95)	(32.38)	(-2.21)		
7	122	0.0003	0.7890**	-	0.809	2.246
		(0.20)	(18.03)			
8	158	0.0004	0.8233**	-	0.696	1.711
		(0.18)	(11.92)			
9	159	-0.0001	0.8497**	-	0.730	1.850
		(-0.06)	(13.15)			
10	261	-0.0024	0.6892**	-	0.283	1.734
		(-0.58)	(7.76)			
11	266	-0.0006	0.6986**	-	0.291	1.856
		(-0.14)	(9.20)			
12	269	0.0004	0.6010**	0.2574**	0.523	2.062
		(0.14)	(10.17)	(3.49)		
13	271	0.0013	0.7003**	-	0.379	1.910
		(0.38)	(8.49)			
14	272	0.0023	0.8103**	-	0.513	1.848
		(0.76)	(11.44)			
15	273	-0.0000	0.7210**	0.1805**	0.521	2.025
		(-0.00)	(10.08)	(2.00)		
16	274	0.0001	0.7294**	0.1843**	0.433	2.044
		(0.03)	(9.01)	(2.21)		
17	275	0.0003	0.7216**	-	0.445	1.637
		(0.10)	(8.77)			
18	276	0.0015	0.7257**	-	0.493	1.849
		(0.55)	(9.40)			
19	277	0.0004	0.6932**	-	0.484	1.933
		(0.14)	(10.00)			
20	278	-0.0017	0.6602**	-0.3105**	0.566	2.055
		(-0.96)	(9.85)	(-2.25)		
21	296	0.0013	0.7151**	-	0.695	2.000
		(0.69)	(14.64)			
22	305	-0.0045**	0.7796**	-	0.670	1.982
		(-2.20)	(12.97)			
23	334	0.0011	0.6541**	-	0.637	1.840
		(0.58)	(12.36)			
24	398	-0.0000	0.9226**	-0.3721**	0.844	2.198
		(-0.01)	(23.10)	(-4.21)		
25	434	0.0018	1.0396**	-	0.594	2.347
		(0.56)	(13.21)			
26	508	-0.0001	0.8475**	-0.3644**	0.841	2.123
		(-0.11)	(22.26)	(-2.86)		
27	524	-0.0016	0.6570**	-	0.332	1.981
		(-0.44)	(7.15)			

	FPG Code	Alpha	Beta	Phi (AR(1))[a]	R-squared	D-W
28	611	-0.0005	1.0201**	-	0.781	2.281
		(-0.26)	(20.27)			
29	613	-0.0062	0.7788**	-	0.101	2.150
		(-0.71)	(4.14)			
30	636	0.0033	0.8771**	-	0.727	1.870
		(1.61)	(19.17)			
31	638	0.0017	0.9263**	-	0.805	2.123
		(0.95)	(18.59)			
32	733	-0.0048	0.6975**	0.2908**	0.530	2.013
		(-1.17)	(8.59)	(3.28)		
33	741	0.0001	0.8214**	-0.2368**	0.771	2.010
		(0.09)	(18.24)	(-2.37)		
34	766	-0.0004	0.9743**	-0.3363**	0.879	2.299
		(-0.39)	(25.68)	(-3.62)		
35	863	0.0012	0.7663**	-	0.593	2.631
		(0.51)	(12.51)			
36	1753	-0.0000	0.6676**	-0.2965**	0.509	2.089
		(-0.01)	(11.36)	(-3.11)		
37	1820	0.0044**	0.6018**	-	0.738	1.709
		(3.23)	(17.29)			

Panel B: Diversified Income Equity Trusts

	FPG Code	Alpha	Beta	Phi (AR(1))[a]	R-squared	D-W
38	31	0.0021	0.6435**	-0.4553**	0.607	2.078
		(1.61)	(17.08)	(-3.46)		
39	33	0.0025*	0.6004**	-	0.718	2.322
		(1.70)	(16.36)			
40	160	0.0016	0.8724**	-	0.794	1.843
		(0.94)	(17.17)			
41	218	0.0043**	0.6190**	-	0.628	1.992
		(2.35)	(15.80)			
42	336	0.0013	0.7805**	-	0.803	2.091
		(0.93)	(14.98)			
43	618	-0.0004	0.8052**	-0.4630**	0.838	2.136
		(-0.37)	(28.75)	(-3.06)		
44	639	0.0014	0.7960**	-	0.703	2.106
		(0.72)	(14.03)			
45	855	0.0011	0.9378**	-	0.823	2.051
		(0.65)	(21.37)			

Panel C: Property Equity Trusts

	FPG Code	Alpha	Beta	Phi (AR(1))[a]	R-squared	D-W
46	337	-0.0045*	0.4011**	-	0.277	1.988
		(-1.84)	(7.32)			
47	366	-0.0031	0.6972**	-	0.313	1.844
		(-0.80)	(7.37)			
48	367	0.0016*	0.0907**	-	0.128	2.108
		(1.87)	(3.08)			
49	401	-0.0039	0.3393**	-	0.169	2.360
		(-1.35)	(4.67)			
50	905	-0.0036	0.1212*	-	0.025	2.004
		(-1.31)	(1.72)			
51	907	-0.0032**	0.0747**	-	0.035	1.695
		(-2.12)	(2.38)			
52	1162	-0.0039	0.3806**	-	0.044	1.624
		(-0.57)	(2.24)			
53	1163	-0.0038	0.6172**	-	0.059	1.858
		(-0.41)	(2.48)			
54	1347	0.0014	0.1576**	-	0.058	1.995
		(0.59)	(2.94)			

Panel D: Diversified Resources Equity Trusts						
	FPG Code	Alpha	Beta	Phi (AR(1))[a]	R-squared	D-W
55	78	-0.0073	0.9620**	-	0.279	1.675
		(-1.24)	(7.30)			
56	161	0.0037	0.7611**	-	0.328	1.668
		(0.86)	(6.04)			
57	267	-0.0117*	1.1341**	-	0.269	1.972
		(-1.72)	(4.36)			
58	637	-0.0030	1.0754**	-	0.606	1.917
		(-0.92)	(12.54)			
59	640	-0.0109	0.8630**	-	0.173	1.985
		(-1.29)	(4.83)			
60	769	0.0001	0.9255**	-	0.515	1.862
		(0.04)	(10.28)			

Panel E: Other Equity Trusts						
	FPG Code	Alpha	Beta	Phi (AR(1))[a]	R-squared	D-W
61	262	0.0034	0.6916**	0.1727**	0.328	1.951
		(0.69)	(6.95)	(2.16)		
62	406	-0.0125**	0.6150**	-	0.141	1.625
		(-2.16)	(4.41)			
63	407	-0.0044	0.6038**	-	0.145	1.746
		(-0.81)	(4.64)			
64	641	0.0050*	0.8311**	-	0.603	1.739
		(1.95)	(12.97)			
65	773	0.0042	0.5115**	0.4294**	0.538	2.104
		(1.04)	(10.15)	(5.11)		

Notes:
a Estimated coefficient on first-order autoregressive error term
b White's (1980) heteroskedasticity adjusted t-statistics in parentheses

** Coefficient is statistically significant at the 5 % level
* Coefficient is statistically significant at the 10 % level

While the full sample of 65 trusts are typically less risky than the market, fourteen reveal a beta estimate insignificantly different from unity. However, in only four cases are the estimates greater than unity. The Diversified Resources category of trusts are typified by the highest beta risk in the sample with five of the six trusts in this category having a beta estimate statistically close to unity. Moreover, this group of trusts produces the highest beta estimate for the full sample, namely, Tyndall Gold Fund (FPG 267). This low maximum value, however, just serves to re-enforce the finding that Australian Equity Trusts over the test period were, if anything, of relatively low risk.

The alpha estimates in the results reported in Table 5.1 reflect the performance of the trusts. It can be seen that in only 5 (10) cases is there any evidence of abnormal performance at the 5 % (10%) level of significance. Of these however, only two (five) showed positive performance at the 5 % (10 %) level of significance. These funds were: (a) Perpetual's Industrial Share Fund (FPG 1820) and BT Select Markets Trust - Equity Imputation (FPG 218) (5 % level) and (b) Advance - Imputation Fund (FPG 33), GEM Property Securities Fund - Income (FPG 367) and National Mutual - Special Situations Fund (FPG 641) (10 % level). On the other hand, the negatively performing funds were: (a) EquitiLink - GrowthLink Trust (FPG 305), AMP - Property Securities Trust (FPG 907) and Tyndall - Global Special Situations Fund (FPG 406) (5 % level) and (b) Tower - Property Securities Trust (FPG 337) and Tyndall - Gold Fund (FPG 267) (10 % level). No other strong patterns emerge from this analysis.

As argued by Sinclair (1990, p. 60), to the extent that trusts successfully engage in market timing activities the standard alpha performance discussed above may not provide the complete story. Accordingly, Tables 5.2 and 5.3 report the outcome of further analysis of the sample of equity trusts that looks for evidence of market timing ability. Specifically, Table 5.2 presents only those cases which provide some evidence of timing ability in the context of the quadratic market model outlined earlier, while Table 5.3 provides the counterpart cases in the context of the dual-beta market model

As can be seen in Table 5.2, there are only eight cases for which any evidence of market timing is detected. Interestingly, in all cases (a) the quadratic term is positive indicating favourable market timing behaviour and (b) the security selection performance (alpha) is negative (although not always significantly so). While the results confirm the negative association between the security selection and market timing performance documented consistently in the literature, this research finds the reverse case to that of Sinclair (1990).

That is, where any evidence of market timing ability at all is found, it is of positive market timing ability, consistent with Bello and Janjigian (1987), as opposed to the finding of "perverse" market timing ability documented by Sinclair (1990).

Table 5.2 Quadratic Excess Returns Market Model Results for Australian Equity Trusts

	FPG Code	Alpha	Beta	Gamma	R-squared	D-W
Panel A: Diversified Growth Equity Trusts						
1	273	-0.0036	0.6983**	2.2771**	0.5330	2.0323
		(-0.88)[a]	(9.73)[a]	(2.21)[a]		
2	274	-0.0037	0.7093**	2.3883*	0.4441	2.0665
		(-0.77)	(8.84)	(1.87)		
3	275	-0.0040	0.6744**	2.5919*	0.4647	1.8964
		(-0.92)	(8.20)	(1.82)		
4	277	-0.0029	0.6801**	2.0304*	0.4943	1.8627
		(-0.91)	(9.58)	(1.67)		
5	741	-0.0037**	0.8103**	2.3248**	0.7871	2.0228
		(-2.29)	(20.23)	(3.38)		
Panel B: Diversified Resources Equity Trusts						
6	267	-0.0315**	1.0561**	12.0461**	0.3464	1.7906
		(-2.98)	(5.62)	(2.05)		
7	637	-0.0071*	1.0592**	2.5136*	0.6141	1.8456
		(-1.84)	(12.85)	(1.87)		
8	640	-0.0217**	0.8226**	6.6086**	0.2000	1.9924
		(-2.14)	(4.68)	(2.41)		

This table shows the results of testing the Quadratic Excess Returns Market Model specified in Equation (5.2): $r_{it} = \alpha_i + \beta_i r_{mt} + \gamma_i r_{mt}^2 + e_{it}$

Notes:

a White's (1980) heteroskedasticity adjusted t-statistics in parentheses

** Coefficient is statistically significant at the 5 % level

* Coefficient is statistically significant at the 10 % level

For four of the funds there is evidence that their managers have had significant market timing ability which has been offset by significantly poor stock selection ability. These cases are: (a) Mercury - Growth Trust (FPG 741); (b) Tyndall - Gold Fund (FPG 267); (c) National Mutual - Resources Fund (FPG 637); and (d) National Mutual - Gold Fund (FPG 640). Comparing these cases back to their overall performance using the standard market model allows quantification of the component of performance attributable to market timing, and in two cases this exceeded 1 % per month. Specifically, Tyndall - Gold Fund (FPG 267) had an overall monthly abnormal performance of -1.17 % (Table 5.2) which decomposes into (a) -3.15 % abnormal return specific to security selection (Table 5.3) and (b) 1.98 % abnormal return specific to market timing activity. Similarly, National Mutual - Gold Fund (FPG 640) had an overall monthly abnormal performance of -1.09 % (Table 5.2) which decomposes into (a) -2.17 % abnormal return specific to security selection (Table 5.3) and (b) 1.08 % abnormal return specific to market timing activity. Overall, there is relatively sparse evidence of any market timing ability across our sample using the quadratic market model approach. An interesting question is whether this conclusion is sensitive to the market timing model applied. This issue is now addressed using the dual-beta market model outlined earlier.

Table 5.3 reveals there are only six cases for which any evidence of market timing is detected based on the dual-beta specification. A comparison with Table 5.2 shows that all of these were identified as market timing performers according to the quadratic market model too. Further, confirming the finding previously, in all cases (a) the ‘down-market’ beta term is positive indicating superior market timing behaviour and (b) the security selection performance (alpha) is negative (although not always significantly so). Hence, the results again confirm the negative association between the security selection and market timing performance documented consistently in the literature.

Table 5.3 Dual-Beta Market Model Results for Australian Equity Trusts

	FPG Code	Alpha	Beta	Gamma	R-squared	D-W
Panel A: Diversified Growth Equity Trusts						
1	273	-0.0057	0.8788**	0.3468*	0.5300	2.0309
		(-1.20)[a]	(7.91)[a]	(1.90)[a]		
2	274	-0.0064	0.9140**	0.3993*	0.4430	2.0617
		(-1.09)	(6.73)	(1.67)		
3	275	-0.0070	0.8982**	0.4346*	0.4638	1.8902
		(-1.30)	(5.51)	(1.70)		
4	741	-0.0058**	0.9942**	0.3580**	0.7831	2.0253
		(-2.25)	(12.56)	(2.46)		
Panel B: Diversified Resources Equity Trusts						
5	267	-0.0416**	1.9888**	1.8029**	0.3247	1.8274
		(-2.82)	(3.33)	(2.03)		
6	640	-0.0335**	1.5099**	1.3610**	0.2092	1.9902
		(-2.64)	(4.93)	(2.55)		

This table shows the results of testing the Dual Beta Market Model specified in Equation (5.4):

$$r_{it} = \alpha_i + \beta_{1i}\, r_{mt} + \beta_{2i}\, D\, r_{mt} + e_{it}$$

Notes:

a White's (1980) heteroskedasticity adjusted t-statistics in parentheses

** Coefficient is statistically significant at the 5 % level

- Coefficient is statistically significant at the 10 % level

For three of the funds there is evidence that their managers have had significant market timing ability which has been offset by significantly poor stock selection ability. These cases are: (a) Mercury - Growth Trust (FPG 741); (b) Tyndall - Gold Fund (FPG 267); and (c) National Mutual - Gold Fund (FPG 640). Specifically, Tyndall - Gold Fund (FPG 267) had an overall monthly abnormal performance of -1.17 % (Table 5.1) which decomposes into (a) -4.16 % abnormal return specific to security selection (Table 5.3) and (b) 2.99 % abnormal return specific to market timing activity. Similarly, National Mutual - Gold Fund (FPG 640) had an overall monthly abnormal performance of -1.09 % (Table 5.1) which decomposes into (a) -3.35 % abnormal return specific to security selection (Table 5.3) and (b) 2.26 % abnormal return specific to market timing activity. Hence, based on the evidence reported in Tables 5.2 and 5.3 regardless of the timing model applied, there is relatively little evidence of any market timing ability across the sample of Australian Equity Trusts.

Attention is now given to the issue of the specification tests of the market timing models, following the suggestions of Jagannathan and Korajczyk (1986). Firstly, this analysis is performed in the context of the quadratic market model. Recall that this produces a cubic market model and the results of this analysis, for those cases in which the cubic term is found to be statistically significant, are reported in Table 5.4.

Table 5.4 Cubic Market Model Results for Australian Equity Trusts

	FPG Code	Alpha	Beta	Gamma	Delta	R-squared	D-W
Panel A: Diversified Growth Equity Trusts							
1	77	-0.0030	1.2094**	-0.1016	-116.1693**	0.4449	1.8863
		(-0.77)[a]	(8.94)[a]	(-0.04)[a]	(-3.91)[a]		
2	82	-0.0044**	1.0690**	1.8360*	-60.5535**	0.7269	2.1021
		(-2.37)	(11.69)	(1.79)	(-2.49)		
3	122	-0.0010	0.8880**	0.8534	-24.7037**	0.8162	2.2117
		(-0.58)	(15.05)	(0.98)	(-2.23)		
4	158	-0.0002	1.0335**	0.4828	-50.4310**	0.7218	1.6741
		(-0.12)	(12.20)	(0.55)	(-5.83)		
5	159	-0.0007	1.0571**	0.4713	-49.7362**	0.7547	1.8549
		(-0.38)	(13.42)	(0.54)	(-5.46)		
6	261	-0.0056	0.4333**	1.8217	51.9407**	0.3243	2.0371
		(-0.83)	(3.41)	(0.92)	(2.26)		
7	271	-0.0014	0.5340**	1.5712	36.8980*	0.4013	1.7847
		(-0.30)	(5.05)	(0.84)	(1.91)		
8	278	-0.0014	0.9480**	-0.0178	-66.0844**	0.6293	2.0983
		(-0.72)	(12.31)	(-0.02)	(-5.29)		
9	733	-0.0053	0.9356**	0.4459	-57.7272**	0.5589	2.0182
		(-1.16)	(8.52)	(0.33)	(-2.98)		
10	1753	0.0004	0.8333**	-0.1526	-37.4213**	0.5302	2.1081
		(0.13)	(10.53)	(-0.13)	(-2.29)		
Panel B: Diversified Income Equity Trusts							
11	160	-0.0001	1.0349**	1.1114	-40.1088**	0.8098	1.7068
		(-0.03)	(15.28)	(1.53)	(-4.15)		
12	336	0.0021	0.9754**	-0.3204	-45.5653**	0.8349	2.0263
		(1.22)	(18.53)	(-0.50)	(-5.66)		
13	639	0.0004	0.9208**	0.6812	-30.5312*	0.7126	2.1581
		(0.18)	(11.06)	(0.71)	(-1.90)		
Panel C: Property Equity Trusts							
14	366	-0.0061	0.8679**	1.9224	-43.2870**	0.3253	1.8557
		(-1.22)	(5.84)	(1.13)	(-2.25)		
15	367	0.0011*	0.1959**	-0.1000	-24.7257**	0.2370	1.8007
		(1.81)	(5.76)	(-0.26)	(-5.20)		
16	1162	-0.0107	0.6694**	4.3356*	-74.8800*	0.0651	1.6353
		(-1.35)	(2.17)	(1.920)	(-1.72)		
17	1163	-0.0109	1.2232**	4.6680*	-150.3476**	0.0917	1.8816
		(-1.11)	(2.75)	(1.66)	(-2.63)		
Panel D: Diversified Resources Equity Trusts							
18	161	0.0013	0.9231**	1.5558	-40.6680*	0.3368	1.6822
		(0.32)	(5.45)	(0.76)	(-1.95)		
19	267	-0.0246**	0.2864	7.3896**	189.0300**	0.4157	1.6805
		(-2.89)	(1.09)	(2.30)	(3.38)		

This table shows the results of testing the Cubic Market Model specified in Equation (5.5):

$$r_{it} = \alpha_i + \beta_i r_{mt} + \gamma_i r_{mt}^2 + \delta_i r_{mt}^3 + e_{it}$$

Notes:

a White's (1980) heteroskedasticity adjusted t-statistics in parentheses

** Coefficient is statistically significant at the 5 % level
* Coefficient is statistically significant at the 10 % level

From Table 5.4 we see that there are fifteen (nineteen) cases, or almost a quarter (29 %) of the sample, that reveal a significant cubic term at the 5 % (10 %) level. This suggests a non-trivial degree of mis-specification of the quadratic market model. Of these cases it is found that the vast majority produce an estimated parameter on the cubic term which is negative. Indeed, only three of the nineteen produce a positive estimated coefficient. Interestingly, only one included trust coincides with the trusts modelled by the quadratic specification results of Table 5.2, namely the Tyndall Gold Fund (FPG 267).

Finally, augmenting the Henriksson and Merton (1981) dual-beta market model is augmented with a quadratic term and the results are presented in Table 5.5. The table reveals that there are eight (eleven) cases in which the coefficient on the augmented variable is significant at the 5 % (10 %) level. Only one of these, namely, IOOF - Equity Common Fund No. 7 (FPG 1753) is common to both sets of significant results reported in Tables 5.4 and 5.5. Interestingly, only one included trust coincides with the trusts modelled by the original Henriksson and Merton (1981) specification results of Table 5.4, namely the Mercury - Growth Trust (FPG 741).

Table 5.5 Augmented Dual-Beta Market Model Results for Australian Equity Trusts

	FPG Code	Alpha	Beta1	Beta2	Gamma	R-squared	D-W
Panel A: Diversified Growth Equity Trusts							
1	76	-0.0137	1.5631**	1.6398	-12.2287*	0.1341	1.6814
		(-0.86)[a]	(2.28)[a]	(1.32)[a]	(-1.84)[a]		
2	120	0.0026	0.7494**	-0.3909*	2.8860**	0.9311	2.0600
		(1.31)	(6.71)	(-1.89)	(2.46)		
3	276	-0.0067	1.2458**	1.0244**	-5.3291**	0.5032	1.8903
		(-1.20)	(4.46)	(1.97)	(-2.01)		
4	278	-0.0083**	1.2712**	1.1815**	-7.9112**	0.5934	2.0596
		(-2.15)	(4.69)	(2.19)	(-2.32)		
5	636	0.0076	0.5189**	-0.6952*	4.4165**	0.7328	1.8545
		(1.57)	(2.36)	(-1.66)	(2.22)		
6	741	-0.0018	0.6913**	-0.2341	3.5616**	0.7879	2.0208
		(-0.49)	(3.48)	(-0.62)	(1.96)		
7	1753	-0.0053	1.1300**	0.8946*	-5.8122*	0.5235	2.0913
		(-1.15)	(4.12)	(1.66)	(-1.73)		
Panel B: Property Equity Trusts							
8	367	-0.0008	0.3293**	0.4603*	-3.1556**	0.1814	1.9862
		(-0.40)	(2.61)	(1.85)	(-2.04)		
Panel C: Diversified Resources Equity Trusts							
9	161	-0.0087	1.4969**	1.4543*	-7.1761**	0.3401	1.6823
		(-1.27)	(3.92)	(1.80)	(-1.96)		
10	769	-0.0111*	1.5928**	1.3193*	-6.4713*	0.5256	1.8503
		(-1.75)	(3.91)	(1.85)	(-1.79)		
Panel D: Other Equity Trusts							
11	406	-0.0300**	2.0139**	2.7210*	-16.8379**	0.1734	1.6158
		(-1.97)	(2.68)	(1.90)	(-2.42)		

This table shows the results of testing the Augmented Dual-Beta Market Model specified in Equation (5.6): $r_{it} = \alpha_i + \beta_{1i} r_{mt} + \beta_{2i} D r_{mt} + \gamma_i r_{mt}^2 + e_{it}$

Notes:

a White's (1980) heteroskedasticity adjusted t-statistics in parentheses

** Coefficient is statistically significant at the 5 % level

* Coefficient is statistically significant at the 10 % level

5.5. Conclusion

Surveys conducted by Lakonishok et al. (1992), Ippolito (1993) and Shukla and Trzcinka (1994) document the renewed interest in portfolio performance and provide an overview of the themes which have emerged in the literature. One important area deals with the evaluation of active portfolio management and asset allocation and, in particular, the identification of market timing ability on the part of fund managers.

The principal issue examined in this chapter therefore was the market timing ability of a segment of the Australian investment fund industry, namely, Australian equity trusts. The approach followed involved running both quadratic excess returns market model and dual-beta excess returns market model regressions. In addition, some specification tests suggested by Jagannathan and Korajczyk (1986) were also applied.

The results suggested that for the sample over the period examined, there is little evidence of market timing ability. Further, there is no clear dominance of one market timing model over the other. It is found however, that a cubic market model specification does fit the data quite well for nearly one third of our sample. This suggests a possible area worthy of further research effort, namely, an examination of performance in the context of higher moment models (see Prakash and Bear 1986; Stephens and Proffitt 1991 and Chunhachinda, Dandapani, Hamid & Prakash 1994)].

While this Chapter found little evidence of successful risk-shifting behaviour in relation to macro-level timing ability, the following two Chapters explore whether tournament theory can be used to establish that fund managers engage in another type of risk-shifting behaviour related to there relative performance ranking each year.

Chapter 6: Tournament Behavior in Australian Superannuation Funds: A Non-parametric Analysis

6.1. Introduction

In a tournament, players compete for prizes where their effort level and their share of the prizes depends upon their ranking. Tournament theory therefore focuses on relative, rather than absolute, performance. Its provenance is in the area of personnel economics, with an initial normative focus on effort responses to the incentive structures specific to rank-order based compensation schemes. Theoretical analysis indicated that under certain circumstances, for example, where participants are risk averse and output disturbances are caused by a common shock, the incentive effects of rank-order compensation schemes are considered to induce optimal levels of effort among participants. The scope of the investigation was soon extended to the issue of whether tournament compensation structures impacted upon participant risk-taking as well as effort responses.

The application of tournament theory to the analysis of managed funds can be understood by looking at the explicit and implicit incentive structures that characterize the industry. First, funds typically charge a management fee that is a fixed percentage of funds under management. Consequently, a goal of fund management companies is to maximize funds under management, and an incentive therefore exists to pursue those strategies that will help achieve that goal.[30] Second, relative fund performance, often highlighted in semi-annual or annual performance or "league" tables, is an important source of information to investors seeking to maximize investment returns. Ippolito (1992), Capon, Fitzsimons and Prince (1996) and, more recently, Wilcox (2003) confirm this in respect of retail fund investors. Third, there appears to be convexity in the flow-performance relationship: Sirri and Tufano

[30] Chordia (1996) and Barclay, Pearson and Weisbach (1998) propose models incorporating different fee structures. However, the ultimate goal remains the maximization of funds under management.

(1992, 1998), Chevalier and Ellison (1997) and Goetzman and Peles (1997) found that while those funds which recorded the highest performance during a period attracted the largest increases in funds under management, those funds which had performed poorly were not penalized by proportionate outflows of funds under management. Similarly, Berkowitz and Kotowitz (2000) found that net new fund investment is positively related to a distributed lag of past fund performance with significant nonlinearity in the performance-fund flow relationship at the extreme levels of performance, particularly for extremely good performance.

Finally, fund manager compensation typically has a variable component related to the performance of the fund over the annual tournament period: an incentive therefore exists for fund managers to invest to maximize tournament period performance.

Given these characteristics, it is not surprising that Brown, Harlow and Starks (1996) [hereafter BHS] applied the tournament model to the funds domain. They hypothesized, and found supporting evidence, that fund managers who were interim losers were likely to increase fund volatility in the latter part of the assessment period to a greater extent than interim winners. Subsequent research, discussed in Section 6.2, failed to confirm conclusively BHS's findings: some studies found that it was interim winners who appeared to increase risk the most in subsequent periods, some found interim winners adopting this behavior, while other studies failed to find support for the tournament effect.

Chapters 6 and 7 explore for evidence of the tournament effect in the behavior of Australian superannuation fund managers over the period 1989-2004. The Australian funds management setting is chosen for this study because it presents a unique opportunity to examine the tournament question. Specifically, in contrast to other markets, three types of tournament might exist since the calendar year, financial/tax year and reporting year may not coincide. Specifically, it is quite common for the Australian financial press to emphasize calendar year investment performance. However, media attention is also focused on fund performance over the July-June period as retail investors typically have June financial (tax) year-ends. As a final complication, in a number of prominent cases, funds adopt an October-September reporting year.

Against this background, this chapter uses a non-parametric methodology to look for evidence of tournament (gaming) behavior in the performance of a group of Australian retail superannuation funds classified as "multi-sector growth funds" by Morningstar. In particular, this chapter investigates the two competing hypotheses put forward in the recent theoretical developments by Taylor (2003), who argued that using an exogenous (endogenous) benchmark, will induce losing (winning) managers to gamble. Accordingly, this research extends the tournaments literature by examining three datasets, based on the calendar year, the financial year and an October-September year, over the period 1989/90 to 2000/01 using a range of within-year assessment periods, against both an exogenous and an endogenous benchmark. Chapter 7 further extends the literature by using parametric regression analysis to investigate the tournament hypothesis and the impact on this hypothesis of a range of conditioning variables.

As with the preceding chapters, a major motivation for choosing an Australian dataset of investment funds is to accommodate the general argument of Leamer (1983) and extended by Lo and MacKinlay (1990) regarding the concern about data snooping in finance research. Moreover, as Australia has the most sophisticated retail funds management market outside the United States, it is appropriate that finance research initially focusing on the US funds management industry should be extended to other developed markets like Australia.

The remainder of this chapter is structured as follows. Section 6.2 provides a review of the most relevant literature. In Section 6.3 the data and research method are described, while Section 6.4 outlines the research goal and hypotheses. The research findings are presented in Section 6.5 and Section 6.6 concludes the paper.

6.2. Literature Review

The literature on tournaments initially focused on employment contracts: Lazear and Rosen (1981) in a seminal paper put forward what has come to be known as the static tournament model, wherein it is assumed that rational, risk-neutral participants decide on an effort level before a single-period tournament begins and cannot alter it afterward. Output levels depend on the work effort provided by the participants plus a random shock that affects the output levels of all participants. Similarly, Holstrom (1982), Green and Stokey (1983) and Nalebuff and Stiglitz (1983) focused on the normative aspects of the tournament model: allowing for participant risk aversion, additive shocks and/or multiplicative shocks, their theoretical analysis indicated that under certain circumstances, the incentive effects of rank-order compensation schemes will induce optimal levels of effort among participants. From an agency theory perspective, Mookherjee (1984) found that where an agent's output depended on a common shock as well as individual effort and idiosyncratic noise, the optimal employment contract may involve relative performance evaluation.

Early empirical research established two important results: First, Bull et al. (1987), examining teams inside firms and Ehrenberg and Bonanno (1990a, 1990b) looking at the PGA golf tournament, reported that effort levels and performance rise as the difference between payoffs to winners and losers increases. Second, participants who are doing poorly in a tournament will adopt high-variance (that is, riskier) strategies. Later research supported these results: For example, Knoeber and Thurman (1994) examined differences in ability among poultry producers and found that disadvantaged participants adopted high-variance strategies in the latter part of the tournament. Oyer (1998) examined revenue seasonality in manufacturing industries characterised by nonlinear compensation contracts for salespeople and executives, and found evidence of fiscal-timing, where agents manipulate revenues to maximise their own incomes.

The extension of the tournament model to the funds management area began with BHS, who characterized the managed funds industry as a multi-period, multi-game tournament[31] and focused on the possible strategic responses of funds identified at interim ranking stages as likely to be ultimate "winners" or "losers". BHS hypothesized that fund managers who were interim losers (below the median performance for the first part of the assessment period), were likely to increase fund volatility in the latter part of the assessment period to a greater extent than interim winners. This strategy of increasing volatility was based on the expectation that higher volatility gave the losing manager a better chance of a major performance reversal that would redeem their ranking and, hence, secure a major tournament prize at year end. While greater volatility also increased the risk of experiencing an even more disastrous full year performance, the losing manager would take the view that because of the tournament nature of the fund industry, coupled with the asymmetric response of money flows to performance, they had nothing much to lose.

BHS's results indicated that losers did indeed appear to gamble, a result confirmed by Koski and Pontiff (1999) looking at US funds and Garcia and Begona (2000) looking at Spanish

[31] The restrictive assumptions of the static tournament model mean that it cannot be validly applied to many real-life situations. In contrast, dynamic tournaments incorporate multiple periods, availability of performance feedback, and alteration of effort levels in response to the feedback during the tournament.

mutual funds. Acker and Duck (2001) extended the two-period model into a signal-extraction framework that incorporates market timing activities by fund managers. They find that managers of losing funds adopt extreme market positions, and that these positions are a positive function of the distance between the fund and the top performer and the fund's assessment of the likely direction of the movement in the equity market. They also found that the tendency to adopt extreme positions increased as the final ranking period approached. Both Goriaev, Palomino and Prat (2001) and Basak, Pavlova and Shapiro's (2002) analyses produced results similar to Acker and Duck (2001). Chen and Pennacchi (2001) developed a model wherein managers adjust the tracking error of the fund in response to performance deviations from a benchmark. Using US data they found that managers increased the tracking error, but not return variance, as performance declines. Kempf and Ruenzi (2003) extend the tournament model to mutual fund families, finding support for the BHS hypothesis in large fund families but finding the opposite result, that is, that winners increase risk the most, in small fund families.

Chevalier and Ellison, (1997) was the first study to document contradictory evidence, suggesting that it is winners rather than losers who gamble, a result confirmed by Qui, (2003). However, Busse (2001), using higher frequency data, was unable to find evidence that intra-year winners or losers actively altered the risk of their portfolio in response to past performance.[32]

Notwithstanding the inconclusive empirical results, recent theoretical developments by Taylor (2003) suggest that the choice of the tournament benchmark for deciding winners and losers

[32] Busse (2001) found no evidence of a tournament effect when examining daily data for US equity funds. He argued that autocorrelation in daily fund returns could bias monthly volatility estimates, leading to the spurious appearance of a tournament effect, and suggested intra-period risk changes were due to changes in the volatility of stock market common risk factors. However, Goriaev, Nijman and Werker (2005) find that tests of the tournament hypothesis based on monthly data are more robust to autocorrelation effects than tests based on daily data. Nevertheless, they also find that cross-correlation in fund returns may lead to spurious tournament effects.

will influence strategic responses by participants. Specifically, he argued that using an exogenous benchmark, such as a sharemarket index, will induce losing managers to gamble while winning managers will index to lock in their lead. In contrast, using an endogenous benchmark, such as the median fund performance, will induce winning managers to gamble. The intuition behind this result is that the winner will expect the loser to gamble so the winner will therefore gamble in order to maintain his or her lead. As the loser recognizes that the winner has a higher probability of success, and given the asymmetric nature of the funds flow-investment performance relationship, the loser also recognizes that the optimum strategy is not to gamble but to index. This result, while contrary to the predictions and empirical findings of BHS is consistent with the results of Chevalier and Ellison (1997) and also the findings of Palomino and Prat (2003) who examine the impact of contract design on fund managers' decisions regarding effort and risk taking.

In a similar vein, Basak, Pavlova and Shapiro's (2002) theoretical analysis shows that in circumstances where the manager's benchmark is less risky than the managers normal portfolio, managers whose performance is ahead of the benchmark towards the end of the tournament have an incentive to reduce their risk and mimic the index. On the other hand, managers whose performance is lagging the index will increase their risk exposure until they reach an extremum at some critical level of underperformance.

While theoretical work into tournament compensation schemes continues (see, for example, Tong and Leung, 2002, and Vandergrift and Brown, 2003), empirical research into risk shifting behavior by fund managers is still inconclusive.

6.3. Research Framework

6.3.1. Superannuation Funds

A superannuation fund is an ongoing fund designed to provide retirement and death benefits to its members. Such funds are an integral part of the retirement income system in Australia. The demographic impact of the ageing of the "baby boomer" generation has meant that government provision of retirement income through a pension scheme would become prohibitively costly. Consequently, access to such a pension has become much more restricted and superannuation has become increasingly important in funding retirement.

Mandatory superannuation contributions for all employees were introduced through Federal Government legislation in July 1992. Since its introduction, employer contributions have risen and they are now required to contribute 9% of an employee's wage to superannuation.[33] The Australian Prudential Regulation Authority (APRA)[34] classifies superannuation funds into the following groups: Corporate (Employer), Industry (Award), Public Sector, Retail (Public Offer) and Small Funds. Table 6.1 provides summary information about these different types of funds.

Table 6.1 Australia's Superannuation Industry June 2001

Type of fund	Assets (AUD $b)	%	Members (millions)	%
Corporate	71.7	15.4	1.4	6.1
Industry	45.0	9.6	6.9	30.3
Public sector	113.9	24.4	2.8	12.3
Retail	158.2	33.9	11.3	49.6
Small Funds	78.2	16.7	0.4	1.8
Total	467.0		22.8	

Source: APRA June 2001 "Superannuation Trends".

[33] The Superannuation Guarantee operates in conjunction with award superannuation. For example, if an award stipulates a superannuation contribution of 6%, then the Superannuation Guarantee requirement would require the employer to contribute an additional 3% to make a total contribution of 9%.
[34] The Australian Prudential Regulation Authority (APRA) is the prudential regulator of the Australian financial services industry. It oversees banks, credit unions, building societies, general insurance and reinsurance companies, life insurance, friendly societies, and most members of the superannuation industry.

As a result of the Australian Government's aggressive retirement provision policies aimed at shifting the burden of funding retirement incomes from the public sector to the private sector, superannuation has become the principal retirement savings vehicle for Australians. Consequently, as reflected by the figures shown in Table 6.1, superannuation funds constitute a significant part of the managed funds industry in Australia.

6.3.2. Data and Sampling

The data were supplied by Morningstar, an independent research house which monitors the managed funds industry. The database consists of monthly index series return data for the period 1989/90 to 2000/01 for retail superannuation funds classified as multi-sector growth and comprises all such funds in existence over this period. A fund was included in the analysis for each full year in which it was present in the database, thereby largely avoiding the major survivorship bias problem created when funds which do not survive for the full sample period are absent from the database.[35]

To be classified as multi-sector, the funds in the sample invest across at least two asset classes, and have between 60 per cent and 80 per cent of their investments allocated to growth oriented assets, defined by Morningstar as equities and property. Growth funds accounted for around 50 per cent of total multi-sector superannuation funds over the period. Such funds present a relevant environment for assessing tournament-type behavior, since managers have a reasonable degree of scope and flexibility to pursue aggressive asset allocation changes.

[35] A number of studies such as Grinblatt and Titman (1989), Brown, Goetzman, Ibbotson and Ross (1992), Carpenter and Lynch (1999) and Carhart, Carpenter, Lynch and Musto (2002) document the economic significance of survivorship bias in studies of equity mutual fund performance, particularly in relation to the issue of persistence in performance. However, and as noted by Del Guercio and Tkac (2002), studies by Sirri and Tufano (1998), Chevalier and Ellison (1997) and Goetzmann and Peles (1997) found that survivorship bias does not affect inferences about the funds flow-performance relationship and, therefore, is not a major issue in studies involving annual tournaments.

For each fund in the sample, data are available from either 1989/90 or the first entire year of operation, if inception is later than this date. The index series reflects changes in the value of an investment in a fund over time, and is based on a notional $10,000 investment in the fund. Monthly index values are calculated by reference to the month-end exit price of the fund, which is net of management fees and assumes reinvestment of all cash and bonus unit distributions. The index series therefore gives representative returns which an actual investor may have achieved and measures the monthly performance of the fund.

Consistent with the theoretical insights of Goriaev et al. (2001) and Taylor (2003), winners/losers are defined in relation to two alternative types of benchmark: (a) an endogenous benchmark – the 'median' manager (that is, being above/below the median performance of similar funds for the first part of the assessment period), and (b) an exogeneous benchmark- the Australian All Ordinaries Accumulation Index (that is, being above/below this market index return for the first part of the assessment period).

Unlike the scenario in the United States where the calendar year and the fiscal year coincide, the Australian fiscal year ends 30 June. Moreover, a number of major Australian financial institutions have reporting years ending 30 September.[36] This means there are three annual tournament scenarios which are not mutually exclusive: (a) calendar year; (b) fiscal year and (c) September year.

Calendar year performance receives substantial coverage in the Australian financial and popular press. Fiscal year performance also receives substantial press coverage and because of domestic taxation implications is the most likely performance period examined by investors

---

[36] The 30 September financial reporting year is a legacy of the reporting year adopted early in the 20th century by a number of banks and insurance offices of British origin. In recent times there has been a move to discard this in favor of a standard financial or calendar year reporting period. For example, in 2003 AXA moved from a September year to a calendar year reporting period.

when reviewing their portfolios. While September year performance receives little attention in the press and is unlikely to be of significance to investors, it may be very relevant to fund managers whose employers report annual profitability on a September basis. The compensation of such fund managers, particularly bonus components, will be affected by September year performance. Accordingly, all three variants of the annual performance year are used in this study.

6.3.3. Some Descriptive Statistics

Table 6.2 provides a summary of some descriptive statistics for the dataset.

Table 6.2 Descriptive Statistics for a Sample of Multi-sector Growth Superannuation Funds

Year	No. of Funds	Financial Year Annual Return Statistics (%) Index (1)	StDev (2)	Median (3)	StDev (4)	Year	No. of Funds	September Year Annual Return Statistics (%) Index (1)	StDev (2)	Median (3)	StDev (4)	Year	No. of Funds	Calendar Year Annual Return Statistics (%) Index (1)	StDev (2)	Median (3)	StDev (4)
1989/90	126	3.5	3.5	9.7	4.1	1989/90	128	-15.1	4.4	0.8	5.6	1990	122	-17.5	4.2	1.4	5.3
1990/91	135	4.1	4.9	8.5	5.7	1990/91	133	17.8	3.5	15.0	5.1	1991	121	34.2	3.8	18.1	7.2
1991/92	129	5.9	4.5	10.0	4.9	1991/92	129	-1.1	3.9	5.1	5.3	1992	129	-2.3	3.6	3.6	4.6
1992/93	139	13.3	3.6	9.9	5.1	1992/93	143	37.5	3.3	21.2	5.1	1993	144	45.4	4.1	23.5	6.1
1993/94	156	9.9	3.8	6.5	3.2	1993/94	158	7.0	5.3	0.0	2.3	1994	169	-8.7	4.3	-6.8	2.1
1994/95	170	18.5	5.5	6.3	3.1	1994/95	175	9.8	4.0	8.6	2.8	1995	179	20.2	3.5	15.1	2.5
1995/96	196	5.7	4.2	9.4	1.8	1995/96	198	11.8	2.9	8.7	1.9	1996	257	13.4	2.6	9.5	1.9
1996/97	216	15.8	2.7	17.2	2.8	1996/97	220	23.9	2.4	17.8	2.8	1997	284	14.7	3.5	12.1	2.4
1997/98	231	25.2	2.8	8.1	2.3	1997/98	233	-1.3	4.1	4.1	2.1	1998	294	10.4	3.7	11.3	2.4
1998/99	260	2.8	3.0	7.4	1.9	1998/99	260	15.4	3.3	8.5	2.3	1999	322	16.1	3.4	8.5	2.4
1999/00	322	15.3	4.3	11.2	2.2	1999/00	272	16.6	3.0	12.9	2.9	2000	337	3.6	2.7	6.4	1.7
2000/01	283	13.7	3.2	4.3	2.0	2000/01	278	-4.7	3.9	-4.1	2.8	2001	294	10.1	4.4	2.1	1.9
2001/02	267	8.8	3.0	-5.5	2.3	2001/02	306	1.6	3.4	-4.5	2.4	2002	312	-8.1	2.5	-8.1	2.9
2002/03	321	-4.5	3.8	-2.6	2.3	2002/03	347	13.1	2.7	5.5	2.5	2003	343	15.9	3.0	6.4	2.3
2003/04	319	-1.1	3.1	12.0	2.4												
Maximum (5)		25.2	5.5	17.2	5.7			37.5	5.3	21.2	5.6			45.4	4.4	23.5	7.2
Minimum (6)		-4.5	2.7	-5.5	1.8			-15.1	2.4	-4.5	1.9			-17.5	2.5	-8.1	1.7
Average (7)		9.1	3.7	7.5	3.1			9.5	3.6	7.1	3.3			10.5	3.5	7.4	3.3
Std. Dev. (8)		7.9		5.6				13.2		7.8				16.8		8.8	

(1) Index is the return on the All-Ordinaries Accumulation Index for the year indicated.
(2) StDev is the standard deviation of the return on the All-Ordinaries Accumulation Index for the year indicated.
(3) Median is the return for the median manager in the sample for the year indicated.
(4) StDev is the standard deviation of the return for the median manager for the year indicated.
(5) Maximum is the highest annual return observed in the benchmark indicated.
(6) Mimimum is the lowest annual return observed in the benchmark indicated.
(7) Average is the arithmetic average of the annual returns.
(8) Std. Dev. is the standard deviation of the annual returns.

The first notable aspect of Table 6.2 is the growth in the number of funds in the sample over the period. The financial year sample grew at an average annual rate of nearly 7% and the September year and Calendar year sample sizes increased at a compound rate of around 8% per year. Our analysis also divides the samples into two roughly equal sub-periods to explore for temporal dynamics in fund manager behavior. When these sub-samples are examined it is evident the growth in funds has likely had a significant impact on the level of competition in the second sub-period. For example, in both the Financial year and the September year samples, the first sub-periods have an average of around 150 funds, compared to around 275 funds in the second sub-period.

We have included information on the behavior over the period of two benchmarks widely used in the analysis of fund manager behavior in Australia. The first is the All-Ordinaries accumulation Index which represents the 500 largest companies listed on the Australian Stock Exchange, and constitutes around 99% of the Australian market. The second benchmark is the median manager, a metric widely used to distinguish "winners" from "losers" in the fund management industry.

As might be expected, the index benchmark displays a greater range of values than the median manager benchmark across each of the tournament years chosen. Interestingly, the average median manager annual returns are similar across each of the tournament years (7.1%-7.5%) but the average index return is at least 1% higher for the Calendar year (10.5%) than the other tournament years (9.1%, 9.5%). Additionally, the range of values for the index and for the median manager in the financial year dataset are much closer to each other than the corresponding figures for the September year data and the Calendar year data. For example, the difference between the highest (lowest) index return and the highest median manager return, annually, is 8.0 (1.0) percentage points in the financial year sample compared to 16.3 (10.6) percentage points in the September year and 21.9 (9.4) percentage points in the calendar year samples. Notably, the standard deviation of the financial year Index annual returns (7.9%) is much closer to that of the median manager annual returns (5.6%) than is the case in the other tournament years, where the difference in magnitude is around 40-50%.

It is also interesting to note that the standard deviation of the annual median manager return has decreased from around five to six per cent in the period up to 1992-93 to around two to three per cent in the period since then. This reduction in volatility is of interest given the increase in the number of funds in the latter part of the sample: one could speculate that an increase in competition would lead to greater return volatility as fund managers chase returns more aggressively in an attempt to get to the front of the pack. However, the evidence indicates that increasing competition has been accompanied by diminished volatility. This finding is also of interest given the risk adjustment metric we use to explore tournament behavior.

The final observation in terms of the descriptive statistics concerns the performance required by a fund to be classified as a winner or a loser based on the fund's annual return. For the sample used in this Chapter, where the exogenous (index) benchmark is used to identify winners and losers, there are nine (out of 35) tournament years in which simply breaking even, that is, earning a zero return, would have been sufficient to classify a fund as a winner. However, there are other years in which a return of around 20 - 30 per cent would be required. For the endogenous benchmark, there are only two instances where a zero annual return would have made a fund a winner and two cases where a return in the 20-25 per cent range was required. Considered from a different perspective, the average median manager return was nearly three percentage points higher than the average index return across the financial, September and calendar years.

6.3.4. Method of Analysis

This chapter applies a non-parametric 'contingency table/ CPR'[37] framework as the basis of The empirical analysis. This choice is founded on several considerations. First, contingency tables are the primary framework within which Brown et al. (1996) perform their investigation. Given that the purpose of this study is to investigate whether their findings hold in a different dataset, for comparability purposes, analysing contingency tables is a natural choice. Second, the application of contingency tables and *CPRs* is common in other areas of the fund performance literature, see for example, Goetzmann and Ibbotson (1994); Kahn and Rudd (1995); Phelps and Detzel (1997). Third, the application of the contingency table approach is quite straightforward and the consequent relative ease of understanding that it affords an audience beyond the academic sphere (e.g. by investment advisors and even everyday investors) is a positive. Such wide-ranging penetration of knowledge is of great appeal in the funds management research area since it holds such obvious and direct interest to investment industry participants. Accordingly, the contingency table/ *CPR* setup is now explained.

[37] CPR stands for Cross-Product Ratio and it will be explained in the text shortly.

Recall that BHS hypothesized that fund managers who are interim losers are likely to increase fund volatility in the latter part of the assessment period to a greater extent than interim winners. This behavior is captured in the predicted relationship between the "risk adjustment ratios" of loser portfolios and winner portfolios:

$$(\sigma_{2L}/\sigma_{1L}) > (\sigma_{2w}/\sigma_{1w}) \tag{6.1}$$

where σ_1 and σ_2 refer to portfolio risk levels in the first and second periods (of each year), respectively, and the subscripts L and W denote loser and winner.

Accordingly, for each performance year two classifications are established: In the first classification interim winners and losers are identified on the basis of the fund's relative return between the commencement of the year and month M, where M ranges from the third month to the ninth month of the relevant year. This means that for each performance year tournament seven interim ranking periods are calculated ranging from three months to nine months. Discrete monthly return data were calculated from the index series produced by Morningstar for each fund. Following BHS, the M-month compound return of each fund 'j', in tournament year 'y', is calculated and denoted as RTN_{jMy}:

$$RTN_{jMy} = [(1+r_{j1y})(1+r_{j2y})\ldots(1+r_{jMy})] - 1 \tag{6.2}$$

where r_{jMy} is the monthly change in the fund's index series value as reported by Morningstar.

In the second classification the 'Risk Adjustment Ratio', RAR, is calculated, which is the ratio of fund volatility before and after the interim assessment period. This measures (relative) changes in the risk of the fund's portfolio and is calculated as:

$$RAR_{jMy} = \sqrt{\left(\frac{\sum_{m=M+1}^{12}\left(r_{jmy} - \bar{r}_{j(12-M)y}\right)^2}{(12-M)-1}\right)} \div \sqrt{\left(\frac{\sum_{M=1}^{M}\left(r_{jmy} - \bar{r}_{jMy}\right)^2}{M-1}\right)} \tag{6.3}$$

The (RTN, RAR) pair is classified for each fund, in each tournament, based upon whether the fund is a (a) Winner (above benchmark return in the assessment period) or Loser (below benchmark return in the assessment period) and (b) whether the fund is High RAR (has increased its risk in the second period i.e. RAR > 1) or Low RAR (has decreased its risk in the second period i.e. RAR < 1). Specifically, cell counts of the four joint RTN/RAR classifications of funds are required: (a) N_{WH} – the number of winning funds with high RAR; (b) N_{WL} – the number of winning funds with low RAR; (c) N_{LH} – the number of losing funds with high RAR; and (d) N_{LL} – the number of losing funds with low RAR. Based on these classifications 2 x 2 contingency tables are generated upon which tests of association are conducted. The non-parametric contingency table analysis is used therefore to identify the frequency with which funds defined as winners or losers during the assessment part of the tournament period, increased or decreased their risk level in the succeeding period.

To test for independence from period to period, the contingency table results can be summarized by the use of the Cross-Product Ratio (Fienberg 1980) or Odds-Ratio (Christensen 1990) which gives the ratio:

$$CPR = \frac{(N_{WH} * N_{LL})}{(N_{WL} * N_{LH})} \tag{6.4}$$

The *CPR* is a basic measure of association for 2 x 2 tables. When *CPR* = 1, it reflects an equal number of observations in each cell of the contingency table and would support the null hypothesis that the two classifications are independent. Alternatively, when *CPR* < 1 (*CPR* > 1), it indicates interim losing managers have increased (decreased) second period risk and interim winners have decreased (increased) risk. The test statistic for the *CPR* is referred to as the z-statistic. It is the standard deviation of the log of the *CPR* and is given by the square root of the sum of the reciprocals of the cell counts. For large samples it is normally distributed with mean log *CPR* and can be used as an alternative to the chi-square statistic to test for independence.

6.4. Tournament Behavior in Australian Superannuation Funds: Research Goal and Hypothesis Development

In this chapter the managed fund literature is extended by investigating an Australian dataset for evidence of tournament behavior. The contribution is related to two specific hypotheses concerning the strategic interaction between active fund managers when alternate benchmarks are specified.

Stated formally, our null hypothesis is that subsequent period fund risk is independent of ranking period performance. Given the research design, failure to reject the null hypothesis would occur when the *CPR* is equal to unity: a *CPR* of one represents equal counts in each of the cells of the contingency table, and indicates an absence of association between fund performance over the assessment period and changes in fund risk over the remaining part of the tournament.

$$H_0: CPR = 1$$

If the null hypothesis of independence between fund performance and subsequent changes in fund risk can be rejected, the alternative hypotheses focus on examining the strategic response of fund managers to performance rankings under different benchmark regimes.[38] First, following Taylor's (2003) game-theoretic analysis, the study investigates whether, under an exogenous benchmark (index) regime, losing managers at the end of the assessment period increase the risk of the fund in the subsequent period while winning managers reduce their risk. Evidence supporting this alternative hypothesis would be provided by a CPR less than unity:

$$H_1: CPR < 1$$

[38] Consistent with earlier literature, Taylor (2003) analyses the strategic response of fund managers in terms of two-person non-cooperative games where one player is the fund manager and the other player represents the benchmark.

Our second alternative hypothesis concerns the strategic response of fund managers when their within tournament performance is assessed against an endogenous benchmark. Under this benchmark regime, Taylor's (2003) analysis predicts that when performance is measured against the median manager, winning managers at the end of the ranking period will increase their portfolio risk over the remaining period while losing managers will reduce their risk. Stated formally:

H_2: CPR > 1

Support for this hypothesis would contradict the findings of BHS but would be consistent with the results reported by Chevalier and Ellison (1997).

This research therefore contributes to the tournaments literature by providing evidence on the different predictions for strategic behavior derived under alternative benchmark regimes used in ranking fund manager performance within tournaments. The hypotheses are tested under three different tournament structures, namely, calendar year, financial year and September year, using a dataset of funds from one of the most sophisticated managed fund markets outside the United States.

6.5. Results

6.5.1. Analysis Relative to an Exogenous Benchmark

The first hypothesis (H_1) is that assessment against an exogenous benchmark, such as a sharemarket index, will induce losing managers to gamble and take on more risk in the subsequent period while winning managers will index to lock in their lead, and in doing so reduce their portfolio risk. This hypothesis is supported where the CPR is less than unity.

Table 6.3 reports the outcome of the contingency table/ CPR analysis applied to Calendar year tournaments assessed against the index benchmark. This table reveals the strongest results in support of H_1. Primary focus in this table should be directed to the bottom row of figures which indicate the aggregate *CPR* results for the complete set of eleven years of Calendar tournaments. Here there is evidence that the overall *CPR* ratio is less than one for all assessment periods – from (3, 9) through to (9, 3).[39] Moreover, all these CPRs are found to be statistically different from (less than) unity at the 5% level, the sole exception being the (8,4) assessment period which, nevertheless, is significant at the 10% level. This evidence is strongly in favor of H_1: in the sample, in the Calendar-year tournaments assessed against an exogenous benchmark, losing (winning) managers appear to gamble (play it safe) and take on more (less) risk in the subsequent period.

[39] Assessment period (M, 12-M) involves an interim period of M months and a 'post' period of 12-M months (M = 3, 4, …, 9). For example, (3, 9) indicates the tournament in which interim performance is based on the first 3 months of the relevant year and the post period is the latter 9 months (i.e. months 4 to 12) of that year.

Table 6.3 Cross-Product Ratios for Calendar-year Tournaments: Index Benchmark

	Assessment Period													
	(3, 9)		(4, 8)		(5, 7)		(6, 6)		(7, 5)		(8, 4)		(9, 3)	
Year	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z
1990	0.33	-0.68	0.33	-0.68	0.33	-0.68	1.00	0.00	0.59	-0.50	1.00	0.00	5.17	1.05
1991	1.02	0.01	1.02	0.01	1.02	0.01	1.02	0.01	0.20	-1.04	0.33	-0.67	1.02	0.01
1992	0.20	-3.76	1.72	0.52	7.46	1.32	2.40	1.70	2.20	2.18	0.61	-0.71	3.00	0.67
1993	0.14	-1.31	0.42	-0.88	0.42	-0.88	1.00	0.00	0.59	-0.50	0.14	-1.31	0.14	-1.31
1994	0.33	-0.68	0.92	-0.23	2.00	2.21	6.69	2.70	0.62	-1.51	0.55	-1.40	1.90	2.06
1995	0.46*	-1.93	0.42	-0.87	2.30	2.74	2.00	2.29	1.86	0.77	1.01	0.01	1.01	0.01
1996	11.96	3.67	1.01	0.00	5.20	1.06	63.81	2.90	0.31	-4.49	1.38	0.90	2.79	2.13
1997	0.91	-0.38	0.91	-0.39	0.14	-1.30	1.00	0.00	0.56	-0.74	3.90	4.56	0.27	-1.43
1998	1.52	1.12	1.07	0.19	1.89	2.28	0.93	-0.20	1.09	0.28	0.98	-0.01	1.72	1.13
1999	0.00	-4.20	0.00	-4.31	0.00	-4.33	0.00	-4.24	0.00	-4.22	0.06	-7.68	0.07	-7.54
2000	0.26	-2.17	1.67	0.49	3.00	0.67	0.41	-3.84	2.24	2.67	1.23	0.75	0.43	-3.63
Total	0.69	-4.45	0.69	-4.29	0.85	-1.90	0.78	-2.86	0.69	-4.39	0.86*	-1.78	0.76	-3.31

Note: This table reports cross-product ratios (CPR) and their associated z-statistics (Z) with reference to Calendar-year tournaments, against an index benchmark. The CPR is calculated as:

$$CPR = \frac{(N_{WH} * N_{LL})}{(N_{WL} * N_{LH})}$$

where: N_{WH} (N_{WL}) is the number of winning funds with high (low) RAR and N_{LH} (N_{LL}) is the number of losing funds with high (low) RAR. The Risk-Adjustment Ratio (RAR) is calculated as:

$$\mathrm{RAR}_{jMy} = \sqrt{\left(\frac{\sum_{m=M+1}^{12} \left(r_{jmy} - \bar{r}_{j(12-M)y} \right)^2}{(12-M)-1} \right)} \div \sqrt{\left(\frac{\sum_{M=1}^{M} \left(r_{jmy} - \bar{r}_{jMy} \right)^2}{M-1} \right)}$$

where RAR_{jMy} (r_{jMy}) is the Risk-Adjustment Ratio (fund monthly return) for fund 'j', over the M-month interim period, in tournament year 'y'. The assessment period (M, 12-M) involves an interim period of M months and a 'post' period of 12-M months (M = 3, 4, …, 9). Winning (Losing) funds are those with interim return performance above (below) the benchmark specified above. High (Low) RAR funds are those with a RAR > 1 (RAR < 1). Lighter shading indicates periods supporting H_1 (at the 5% level) i.e. where interim Winners (Losers) have decreased (increased) second period risk (i.e. $CPR < 1$). Darker shading indicates periods supporting H_2 (at the 5% level) i.e. where interim Winners (Losers) have increased (decreased) second period risk (i.e. $CPR > 1$). * indicates significant at the 10% level.

Due to maximizing the effective sample size, the aggregate results discussed above provide the most powerful and, hence, the most reliable test of the tournament hypothesis. Nevertheless, it is of interest and worthwhile making a guarded micro-assessment of the individual results – keeping a particular eye out for any patterns or trends that may provide further insights into tournament-type behavior in the sample. To this end, further examination of Table 6.3, does present some supplementary findings. First, it is apparent that some variation in the effect occurs over time and across assessment periods. Within the 77 individual calendar year tournaments, there were 12 instances each of a significant *CPR* less than one and greater than one (at the 5% level). Second, the tournament of 1999 is a 'stand-out' in the sense that it was the only year in which each assessment period had individual *CPRs* less than one, and all were significant at the 5% level.

Third, is the question of whether any 'within-tournament' patterns or trends reveal themselves? Very little can be detected in this regard, although perhaps there is a weak pattern in which assessment periods with shorter (longer) interim periods tend (not) to support H_1. To the extent that such an effect is real, it would be consistent with losing/winning fund managers being more likely to act earlier (or not at all). Fourth, relates to the question of whether there are any 'across-year' patterns or trends which might suggest changing behavior over time? Again, there is very little to go on here. There does however, appear to be a concentration of support for H_1 in the latter two years of our sample, which may suggest that while fund managers historically were not susceptible to the gaming behavior, they may have changed in recent years (perhaps due to increasing competition in the industry). However, this is only conjecture based on our limited sample and evidence. To be confirmed, it would require extended examination in future research.

The final and overall comment with regard to the Table 6.3 results is that while strong (aggregate) support is found for H_1, the volatility underlying this finding warrants a careful qualification to the conclusion that can be drawn from this analysis. In particular, the extent to which this gaming behavior occurs (for Calendar/index benchmark tournaments), either (a) it is a more long-term in nature or (b) it is largely a recent phenomenon (with no guarantee of continuation). Either way, given the limited evidence to date, it will be difficult to predict over any short-term horizon.

The counterpart September-year and Financial-year results for the exogenous benchmark were far less conclusive.[40] With regard to the September-year analysis, only nine significant *CPR* results (at the 5% level) emerged from the 84 individual tournaments. However, it is notable that seven of these cases favored H_1 i.e. they indicated that interim losers increased risk. Furthermore, in turn, three of these cases were recorded for the (8,4) tournament periods in 1991/92, 1990/2000 and 2000/2001. Moreover, the only overall *CPR* that was significant at the 5% level was the (8,4) period which recorded a *CPR* of 0.67. The Financial-year exogenous benchmark analysis returned only six significant *CPR* results from the 84 individual tournaments. Again, H_1 was the main beneficiary, with five of these cases indicating that interim losers (winners) increased (reduced) risk. However, at an aggregate level no tournament assessment period recorded a significant overall CPR.

Taken together, all of the analysis involving exogenous benchmarks does provide a degree of support favoring H_1. This is particularly so for the Calendar-year results and suggests that the extent to which fund managers in the sample are 'tournament-conscious', they probably view the Calendar year as most important. This is consistent with the argument mounted earlier that

[40]The results for these two cases are reported in Appendix 6.1 and Appendix 6.2, respectively.

Calendar-year investment performance is given considerable prominence by the Australian financial press.

6.5.2. Analysis Relative to an Endogenous Benchmark

The second hypothesis (H_2) is that assessment against an endogenous benchmark, such as a median performance, will induce winning (losing) managers to take on more (less) risk in the subsequent period. This hypothesis is supported where the *CPR* exceeds unity.

At a general level, the results for the endogenous (median manager) benchmark produced a greater number of significant results compared to the exogenous benchmark. In both the Calendar Year and the Financial Year, 43 percent of the individual tournaments recorded significant results while in the September year the comparable figure was 39 percent. More specific details are discussed below.

Table 6.4 reports the outcome for the September-year results for the endogenous benchmark. This analysis returned 33 significant *CPR* results from the 84 individual tournaments. Of these cases, 24 indicated that interim period losers increased risk in the second period – thereby providing support for H_1. Moreover, the overall *CPR* results revealed the same behavior in five of the seven assessment periods (at the 5% level), with the (3,9) and (8,4) periods being the exceptions, although the latter of these two cases was significant at the 10% confidence level. The concentration of significant below unity *CPR* results in the individual annual tournaments was highest at five (out of 12 years) in the (4,8) period, with four of those results recorded consecutively in the years 1992/93 to 1995/96. Interestingly, the last three years of the dataset reveal a similar concentration in the (9,3) assessment period. The year 1992/93 is notable in as much as the first five assessment periods record significant *CPR* results. That year recorded the highest median manager return of 21.2 percent. At first sight this would suggest that buoyant market conditions created high performance pressures on managers. However, a similar pattern is not evident in 1996/97, the year with the next highest median manager return of 17.8 percent.

Table 6.4 Cross-Product Ratios for September-year Tournaments: Median Benchmark

	Assessment Period													
	(3, 9)		(4, 8)		(5, 7)		(6, 6)		(7, 5)		(8, 4)		(9, 3)	
Year	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z
1989/90	1.00	0.00	1.00	0.00	0.78	-0.71	0.41	-2.45	0.88	-0.35	0.88	-0.35	0.60	-1.41
1990/91	0.91	-0.26	1.03	0.09	1.31	0.78	1.89	1.81	1.67	1.47	1.89*	1.81	0.81	-0.61
1991/92	0.14	-4.99	1.50	1.14	1.17	0.44	2.19	2.19	0.49	-2.01	1.50	1.14	1.32	0.79
1992/93	0.39	-2.74	0.31	-3.38	0.49	-2.08	0.49	-2.08	0.39	-2.74	0.78	-0.75	0.78	-0.75
1993/94	0.57	-1.74	0.21	-4.50	0.86	-0.48	2.97	3.30	0.63	-1.43	0.95	-0.16	0.86	-0.48
1994/95	1.86	2.03	0.47	-2.48	0.56*	-1.88	0.23	-4.51	0.47	-2.48	0.74	-0.98	1.17	0.53
1995/96	0.46	-2.68	0.30	-4.06	0.59*	-1.84	0.89	-0.43	0.59*	-1.84	1.22	0.71	1.22	0.71
1996/97	2.83	3.73	1.34	1.08	0.52	-2.42	0.75	-1.08	0.93	-0.27	0.60*	-1.88	0.38	-3.47
1997/98	0.72	-1.24	1.25	0.85	1.09	0.33	0.95	-0.20	1.34	1.11	1.17	0.59	1.77	2.15
1998/99	1.98	2.72	1.45	1.49	0.50	-2.72	0.50	-2.72	0.65*	-1.73	0.57	-2.23	0.39	-3.69
1999/00	2.61	3.84	1.81	2.42	0.89	-0.49	0.89	-0.49	0.89	-0.49	0.34	-4.31	0.55	-2.42
2000/01	0.77	-1.08	0.61	-2.03	1.46	1.56	0.92	-0.36	0.48	-2.98	1.37	1.32	0.43	-3.45
Total	0.95	-0.57	0.82	-2.42	0.80	-2.76	0.83	-2.26	0.72	-4.00	0.86*	-1.84	0.72	-3.91

Note: This table reports cross-product ratios (CPR) and their associated z-statistics (Z) with reference to September-year tournaments, against a median benchmark. The CPR is calculated as:

$$CPR = \frac{(N_{WH} * N_{LL})}{(N_{WL} * N_{LH})}$$

where: N_{WH} (N_{WL}) is the number of winning funds with high (low) RAR and N_{LH} (N_{LL}) is the number of losing funds with high (low) RAR. The Risk-Adjustment Ratio (RAR) is calculated as:

$$\mathrm{RAR}_{jMy} = \sqrt{\left(\frac{\sum_{m=M+1}^{12}\left(r_{jmy} - \bar{r}_{j(12-M)y}\right)^2}{(12-M)-1}\right)} \div \sqrt{\left(\frac{\sum_{M=1}^{M}\left(r_{jmy} - \bar{r}_{jMy}\right)^2}{M-1}\right)}$$

where RAR_{jMy} (r_{jMy}) is the Risk-Adjustment Ratio (fund monthly return) for fund 'j', over the M-month interim period, in tournament year 'y'. The assessment period (M, 12-M) involves an interim period of M months and a 'post' period of 12-M months (M = 3, 4, …, 9). Winning (Losing) funds are those with interim return performance above (below) the benchmark specified above. High (Low) RAR funds are those with a RAR > 1 (RAR < 1). Lighter shading indicates periods supporting H_1 (at the 5% level) i.e. where interim Winners (Losers) have decreased (increased) second period risk (i.e. *CPR* < 1). Darker shading indicates periods supporting H_2 (at the 5% level) i.e. where interim Winners (Losers) have increased (decreased) second period risk (i.e. *CPR* > 1). * indicates significant at the 10% level

.

The basic thrust of the September/ Median Benchmark results provides reasonably strong support for H_1, contrary to the prediction (based on Taylor, 2003) of H_2, namely, that interim winners (losers) will increase (decrease) risk. There is however, some weak evidence that may point to this latter hypothesis being relevant in the latter years of the sample. Specifically, in the years 1994/95, 1996/97, 1998/99 and 1999/00 the *CPR* significantly exceeds unity (at the 5% level) for the (3,9) period, possibly suggesting that winning (losing) managers are more likely to act earlier to increase (decrease) risk.

The Financial-year analysis for the endogenous benchmark is shown in Table 6.5. Again, initial attention should be directed to the bottom row of figures which indicate the aggregate *CPR* results for the complete set of twelve years. Here the results show that the overall *CPR* ratio exceeds unity in all but two cases, but in both of those it is very close to unity. Of these aggregate *CPRs*, two are statistically significant and greater than unity (at the 5% level) – namely, the (3,9) and (8,4) cases. This represents reasonable support in favor of H_2, consistent with the prediction of Taylor's (2003) model for the endogenous benchmark case. When the individual results are more closely assessed, 36 (44) of the 84 individual tournaments were significant at the 5% (10%) level. Notably, a considerable majority of 21 (29) cases indicate that it was the interim winners (losers) who subsequently increased (reduced) their risk. This provides substantial reinforcing support for H_2, just as predicted for analysis based on endogenous benchmarks. While the individual tournament period results do not reveal a pattern of concentration within any assessment period, it is notable that 10 of the significant *CPRs* greater than unity are recorded in the two years 1996/97 and 1997/98.

Table 6.5 Cross-Product Ratios for Financial-year Tournaments: Median Benchmark

	Assessment Period													
	(3, 9)		(4, 8)		(5, 7)		(6, 6)		(7, 5)		(8, 4)		(9, 3)	
Year	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z
1989/90	0.56	-1.60	0.73	-0.89	0.56	-1.60	0.73	-0.89	1.21	0.53	1.07	0.18	0.94	-0.18
1990/91	3.74	3.63	1.39	0.95	1.39	0.95	2.25	2.31	2.89	2.98	2.25	2.31	1.76*	1.63
1991/92	1.93*	1.84	0.91	-0.26	0.43	-2.36	0.38	-2.70*	0.63	-1.32	0.71	-0.97	0.71	-0.97
1992/93	0.69	-1.10	0.87	-0.42	0.30	-3.43	0.77	-0.76	0.69	-1.10	0.48	-2.11	0.38	-2.77
1993/94	1.11	0.32	1.67	1.60	1.51	1.28	0.81	-0.64	0.25	-4.08	0.90	-0.32	1.67	1.60
1994/95	0.30	-3.78	0.49	-2.29	2.25	2.59	1.68*	1.68	0.65	-1.38	0.65	-1.38	0.33	-3.48
1995/96	1.00	0.00	0.37	-3.39	0.85	-0.57	1.28	0.86	1.28	0.86	1.78	1.99	1.78	1.99
1996/97	2.47	3.24	2.12	2.71	1.68*	1.90	3.68	4.55	3.13	4.03	1.35	1.09	1.68*	1.90
1997/98	2.45	3.33	3.06	4.09	1.98	2.55	1.84	2.29	1.60*	1.77	1.72	2.03	2.64	3.58
1998/99	2.40	3.45	0.73	-1.24	1.28	0.99	0.47	-2.96	0.61	-1.98	1.64	1.98	1.06	0.25
1999/00	1.00	0.00	0.83	-0.74	1.63	1.96	1.53*	1.72	1.73	2.21	1.53*	1.72	1.06	0.25
2000/01	0.87	-0.60	0.55	-2.49	0.23	-5.71	0.69	-1.55	1.45	1.55	0.87	-0.60	0.46	-3.20
Total	1.26	2.75	0.94	-0.75	0.97	-0.33	1.11	1.25	1.13	1.50	1.18	2.00	1.02	0.25

Note: This table reports cross-product ratios (CPR) and their associated z-statistics (Z) with reference to Financial-year tournaments, against a median benchmark. The CPR is calculated as:

$$CPR = \frac{(N_{WH} * N_{LL})}{(N_{WL} * N_{LH})}$$

where: N_{WH} (N_{WL}) is the number of winning funds with high (low) RAR and N_{LH} (N_{LL}) is the number of losing funds with high (low) RAR. The Risk-Adjustment Ratio (RAR) is calculated as:

$$\mathrm{RAR}_{jMy} = \sqrt{\left(\frac{\sum_{m=M+1}^{12}\left(r_{jmy} - \bar{r}_{j(12-M)y}\right)^2}{(12-M)-1}\right)} \div \sqrt{\left(\frac{\sum_{M=1}^{M}\left(r_{jmy} - \bar{r}_{jMy}\right)^2}{M-1}\right)}$$

where RAR_{jMy} (r_{jMy}) is the Risk-Adjustment Ratio (fund monthly return) for fund 'j', over the M-month interim period, in tournament year 'y'. The assessment period (M, 12-M) involves an interim period of M months and a 'post' period of 12-M months (M = 3, 4, …, 9). Winning (Losing) funds are those with interim return performance above (below) the benchmark specified above. High (Low) RAR funds are those with a RAR > 1 (RAR < 1). Lighter shading indicates periods supporting H_1 (at the 5% level) i.e. where interim Winners (Losers) have decreased (increased) second period risk (i.e. *CPR* < 1). Darker shading indicates periods supporting H_2 (at the 5% level) i.e. where interim Winners (Losers) have increased (decreased) second period risk (i.e. *CPR* > 1). * indicates significant at the 10% level.

The Calendar-year analysis is revealed in Table 6.6. In broad terms the results are quite similar to the counterpart Financial-year results just discussed, again with some reasonable support for H_2. As such, only a few brief additional comments will be made here. It does seem that, if anything, H_2 is a little less favored here than in the previous Financial-year analysis. Specifically, while 32 (39) of the 77 individual tournaments record significant *CPRs*, 14 (16) cases support H_1, i.e. they indicate interim losers (winners) increase (decrease) second period risk and 18 (23) cases indicate the opposite i.e. support for H_2 at the 5% level (10% level) of significance. This is a little more balanced split than was observed above for the Financial-year analysis. The overall *CPR* results show losers increasing risk in the (4,8) assessment period and the winners increasing risk in the (8,4) and (9,3) periods. Moreover, it does seem that support for H_2 is generally concentrated in these longer interim period tournaments – there are five (four) such individual year *CPRs* that are significantly greater than unity for (8,4) and (9,3), respectively. This is suggestive that winning (losing) managers are more likely to act later to increase (decrease) risk in this Calendar-year setting.

Table 6.6 Cross-Product Ratios for Calendar-year Tournaments: Median Benchmark

	Assessment Period													
	(3, 9)		(4, 8)		(5, 7)		(6, 6)		(7, 5)		(8, 4)		(9, 3)	
Year	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z
1990	0.55	-1.62	0.55	-1.62	0.82	-0.54	0.42	-2.34	0.82	-0.54	1.07	0.18	3.14	3.04
1991	0.69	-1.00	0.46	-2.08	1.18	0.45	1.18	0.45	2.02*	1.90	1.54	1.18	0.53*	-1.72
1992	0.25	-3.71	1.93*	1.84	1.70	1.49	2.19	2.19	2.19	2.19	1.50	1.14	2.50	2.53
1993	0.45	-2.32	0.80	-0.67	0.72	-1.00	1.96	1.99	0.89	-0.33	1.96	1.99	1.00	0.00
1994	1.50	1.31	1.13	0.38	1.81*	1.92	0.93	-0.23	0.70	-1.15	0.77	-0.85	1.65	1.61
1995	0.98	-0.08	1.84	2.01	2.42	2.89	2.01	2.30	1.68*	1.71	2.01	2.30	1.53	1.42
1996	1.22	0.81	0.51	-2.67	1.11	0.43	1.08	0.31	0.31	-4.49	0.70	-1.43	0.90	-0.44
1997	1.49*	1.66	0.62	-2.01	1.18	0.71	0.31	-4.68	0.33	-4.45	10.09	8.31	4.65	6.02
1998	1.07	0.29	0.49	-2.96	0.73	-1.34	2.47	3.76	1.16	0.64	5.99	6.95	1.10	0.41
1999	0.84	-0.78	1.10	0.45	1.16	0.68	1.10	0.45	1.87	2.78	2.99	4.74	1.69	2.34
2000	0.73	-1.47	0.69*	-1.69	0.45	-3.63	0.45	-3.63	1.98	3.09	0.53	-2.88	0.60	-2.34
Total	0.87	-1.63	0.78	-3.03	1.02	0.19	0.98	-0.27	1.02	0.27	1.83	7.24	1.37	3.85

Note: This table reports cross-product ratios (CPR) and their associated z-statistics (Z) with reference to Calendar-year tournaments, against a median benchmark. The CPR is calculated as:

$$CPR = \frac{(N_{WH} * N_{LL})}{(N_{WL} * N_{LH})}$$

where: N_{WH} (N_{WL}) is the number of winning funds with high (low) RAR and N_{LH} (N_{LL}) is the number of losing funds with high (low) RAR. The Risk-Adjustment Ratio (RAR) is calculated as:

$$\mathrm{RAR}_{\mathrm{jMy}} = \sqrt{\left(\frac{\sum_{m=M+1}^{12}\left(r_{jmy} - \bar{r}_{j(12-M)y}\right)^2}{(12-M)-1}\right)} \div \sqrt{\left(\frac{\sum_{M=1}^{M}\left(r_{jmy} - \bar{r}_{jMy}\right)^2}{M-1}\right)}$$

where $\mathrm{RAR}_{\mathrm{jMy}}$ (r_{jMy}) is the Risk-Adjustment Ratio (fund monthly return) for fund 'j', over the M-month interim period, in tournament year 'y'. The assessment period (M, 12-M) involves an interim period of M months and a 'post' period of 12-M months (M = 3, 4, …, 9). Winning (Losing) funds are those with interim return performance above (below) the benchmark specified above. High (Low) RAR funds are those with a RAR > 1 (RAR < 1). Lighter shading indicates periods supporting H_1 (at the 5% level) i.e. where interim Winners (Losers) have decreased (increased) second period risk (i.e. *CPR* < 1). Darker shading indicates periods supporting H_2 (at the 5% level) i.e. where interim Winners (Losers) have increased (decreased) second period risk (i.e. *CPR* > 1). * indicates significant at the 10% level.

Viewed as a package, the analysis involving endogenous benchmarks is quite supportive of H_2. This is particularly so for the Financial-year investigations (and to a lesser extent also with the Calendar-year results). Once again, this is consistent with the argument mounted earlier that Financial and Calendar-year investment performance is given considerable prominence by the Australian financial press and investors.

6.6. Summary and Conclusion

The funds management industry has proven to be fertile ground for theoretical and empirical research over the past forty years. Since the performance and risk-shifting behavior of fund managers was initially put under the spotlight by Treynor and Mazuy (1966) and Jensen (1968), it is possible to identify an evolving strand in the research where performance assessment is examined within the framework of the principal-agent literature. One focus that has emerged in this literature is the tournament model developed by Brown et al. (1996). Specifically, they hypothesized that fund managers who were interim losers were likely to increase fund volatility in the latter part of the assessment period to a greater extent than interim winners. While the empirical results are mixed, recent theoretical developments by Taylor (2003) argue that using an exogenous (endogenous) benchmark, will induce losing (winning) managers to gamble. This presents two competing testable hypotheses.

Using a sample period covering 1989 to 2001, this chapter investigated the tournament induced risk-shifting behavior of Australian “multi-sector growth funds”. Specifically, following Taylor (2003), the ability of the two competing hypotheses to predict risk-shifting behavior in the sample was tested. To this end, the non-parametric Cross-Product Ratio methodology was applied to examine tournaments based on the calendar year, the financial year and an October-September year, using a range of within-year assessment periods, against both an exogenous and an endogenous benchmark.

The research findings can be summarized as follows. At a broad level the study found evidence in support of Taylor's model. Specifically, when an exogenous benchmark is used (i.e. market index return), support was uncovered for the hypothesis that losing managers at the end of the interim assessment period increase the risk of the fund in the subsequent period, while winning managers reduce their risk (H_1). This support is particularly evident for the Calendar-year analysis. However, the volatility underlying this finding warrants a careful qualification to the conclusion that can be drawn from this analysis. In particular, the extent to which this gaming behavior occurs (for Calendar/index benchmark tournaments), either (a) it is a more long-term in nature or (b) it is largely a recent phenomenon (with no guarantee of continuation). Either way, given the limited evidence to date, it will be difficult to predict over any short-term horizon.

The second hypothesis (H_2) which comes from the Taylor (2003) model, is that assessment against an endogenous benchmark, such as a median fund performance, will induce winning (losing) managers to take on more (less) risk in the subsequent period. Viewed as a whole, the analysis involving endogenous benchmarks is also quite supportive of H_2. This is particularly so for the Financial-year investigations (and to a lesser extent also with the Calendar-year results). Once again, this is consistent with the view that the Australian financial press and investors are particularly fixated on Financial and Calendar-year investment performance.

The research in this chapter therefore extends the empirical literature on fund manager behavior, by seeking evidence of tournament effects in a dataset from one of the most sophisticated funds management market outside the United States. Moreover, the study employed three different representations of the annual tournament period and examined behavior against two ranking benchmarks, one endogenous and one exogenous. While the study is concerned primarily with evidence of risk-taking behavior on the part of fund managers, it can also be viewed as providing, albeit indirectly, empirical evidence on the question of whether benchmark choice may affect such behavior.

Chapter 7 continues the examination of tournament behaviour by using a more powerful parametric regression-based methodology to examine risk-shifting behaviour by fund managers.

Appendix 6.1: Cross-Product Ratios for September-year Tournaments: Index Benchmark

	Assessment Period													
	(3, 9)		(4, 8)		(5, 7)		(6, 6)		(7, 5)		(8, 4)		(9, 3)	
Year	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z
1989/90	2.41	0.89	2.16	0.98	1.00	0.00	0.33	-0.68	0.33	-0.68	0.33	-0.68	0.33	-0.68
1990/91	0.98	-0.01	2.37	0.87	1.31	0.61	1.89	1.73	1.16	0.29	5.23	1.06	0.78	-0.68
1991/92	0.22	-1.66	1.11	0.25	0.88	-0.33	3.48	3.04	0.78	-0.34	0.15	-3.11	1.55	1.06
1992/93	1.01	0.01	0.34	-2.28	1.01	0.01	0.60	-0.49	0.60	-0.49	0.60	-0.49	0.60	-0.49
1993/94	0.33	-0.68	0.19	-1.05	0.09	-1.66	0.54	-0.76	0.09	-1.66	0.26	-1.45	0.16	-2.03
1994/95	0.99	-0.02	0.99	-0.02	0.62	-0.85	0.99	-0.02	0.48	-2.35	0.56	-1.20	1.53	0.90
1995/96	0.26	-1.44	3.03	0.68	1.00	0.00	1.84	0.76	1.00	0.00	0.33	-0.68	1.41	0.41
1996/97	1.00	0.00	0.33	-0.68	0.71	-0.41	1.00	0.00	1.04	0.02	1.00	0.00	1.00	0.00
1997/98	0.99	0.00	0.99	0.00	0.99	0.00	0.99	-0.01	3.05	1.17	0.99	0.00	3.00	0.67
1998/99	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
1999/00	1.00	0.00	1.00	0.00	0.44	-1.05	0.80	-0.75	0.97	-0.12	0.27	-5.04	9.27	1.49
2000/01	1.57	1.24	1.27	0.69	0.24	-4.08	10.67	2.73	1.00	0.00	0.08	-4.85	0.33	-0.68
Total	1.16	1.74	0.97	-0.31	0.85	-1.85	1.11	1.30	0.92	-0.93	0.67	-4.48	1.00	0.02

Note: This table reports cross-product ratios (CPR) and their associated z-statistics (Z) with reference to September-year tournaments, against an index benchmark. The CPR is calculated as:

$$CPR = \frac{(N_{WH} * N_{LL})}{(N_{WL} * N_{LH})}$$

where: N_{WH} (N_{WL}) is the number of winning funds with high (low) RAR and N_{LH} (N_{LL}) is the number of losing funds with high (low) RAR. The Risk-Adjustment Ratio (RAR) is calculated as:

$$\mathrm{RAR}_{jMy} = \sqrt{\left(\frac{\sum_{m=M+1}^{12}\left(r_{jmy} - \bar{r}_{j(12-M)y}\right)^2}{(12-M)-1}\right)} \div \sqrt{\left(\frac{\sum_{M=1}^{M}\left(r_{jmy} - \bar{r}_{jMy}\right)^2}{M-1}\right)}$$

where RAR_{jMy} (r_{jMy}) is the Risk-Adjustment Ratio (fund monthly return) for fund 'j', over the M-month interim period, in tournament year 'y'. The assessment period (M, 12-M) involves an interim period of M months and a 'post' period of 12-M months (M = 3, 4, …, 9). Winning (Losing) funds are those with interim return performance above (below) the benchmark specified above. High (Low) RAR funds are those with a RAR > 1 (RAR < 1). Lighter shading indicates periods supporting H_1 (at the 5% level) i.e. where interim Winners (Losers) have decreased (increased) second period risk (i.e. *CPR* < 1). Darker shading indicates periods supporting H_2 (at the 5% level) i.e. where interim Winners (Losers) have increased (decreased) second period risk (i.e. *CPR* > 1). * indicates significant at the 10% level.

Appendix 6.2: Cross-Product Ratios for Financial-year Tournaments: Index Benchmark

	Assessment Period													
	(3, 9)		(4, 8)		(5, 7)		(6, 6)		(7, 5)		(8, 4)		(9, 3)	
Year	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z	CPR	Z
1989/90	3.05	0.68	3.05	0.68	0.80	-0.33	1.00	0.00	2.41	0.89	1.06	0.18	1.63	0.84
1990/91	1.15	0.25	0.19	-1.06	0.99	-0.01	1.67	0.49	0.98	-0.02	1.86	1.43	1.12	0.22
1991/92	0.24	-2.23	0.33	-0.67	4.78	1.69	1.89	0.79	0.78	-0.49	1.02	0.04	2.40	1.70
1992/93	0.32	-0.69	0.32	-0.69	0.32	-0.69	1.40	0.40	2.37	0.87	0.43	-1.40	0.34	-2.55
1993/94	0.33	-0.68	1.03	0.01	3.04	0.68	1.00	0.00	1.00	0.00	3.04	0.68	1.69	0.50
1994/95	3.04	0.68	1.00	0.00	1.11	0.23	1.00	0.00	0.81	-0.33	0.45	-2.22	0.31	-2.69
1995/96	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
1996/97	1.76	1.82	7.20	1.30	0.19	-1.84	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
1997/98	1.31	0.88	0.99	0.00	0.99	0.00	0.33	-0.68	4.49	1.64	3.11	1.53	1.94	1.11
1998/99	4.05	3.55	0.94	-0.25	0.42	-0.88	1.99	1.27	0.42	-0.88	1.00	0.00	0.33	-0.68
1999/00	0.20	-1.05	0.55	-0.76	1.32	1.12	1.00	0.00	1.54	1.22	1.17	0.56	1.14	0.51
2000/01	0.50	-1.71	1.00	0.00	0.32	-2.41	0.54	-1.20	1.43	1.46	0.84	-0.71	1.59	0.67
Total	1.07	0.84	0.99	-0.16	0.98	-0.29	1.01	0.07	1.08	0.92	0.97	-0.32	0.98	-0.29

Note: This table reports cross-product ratios (CPR) and their associated z-statistics (Z) with reference to Financial-year tournaments, against an index benchmark. The CPR is calculated as:

$$CPR = \frac{(N_{WH} * N_{LL})}{(N_{WL} * N_{LH})}$$

where: N_{WH} (N_{WL}) is the number of winning funds with high (low) RAR and N_{LH} (N_{LL}) is the number of losing funds with high (low) RAR. The Risk-Adjustment Ratio (RAR) is calculated as:

$$\mathrm{RAR}_{jMy} = \sqrt{\left(\frac{\sum_{m=M+1}^{12} \left(r_{jmy} - \bar{r}_{j(12-M)y} \right)^2}{(12-M)-1} \right)} \div \sqrt{\left(\frac{\sum_{M=1}^{M} \left(r_{jmy} - \bar{r}_{jMy} \right)^2}{M-1} \right)}$$

where RAR_{jMy} (r_{jMy}) is the Risk-Adjustment Ratio (fund monthly return) for fund 'j', over the M-month interim period, in tournament year 'y'. The assessment period (M, 12-M) involves an interim period of M months and a 'post' period of 12-M months (M = 3, 4, …, 9). Winning (Losing) funds are those with interim return performance above (below) the benchmark specified above. High (Low) RAR funds are those with a RAR > 1 (RAR < 1). Lighter shading indicates periods supporting H_1 (at the 5% level) i.e. where interim Winners (Losers) have decreased (increased) second period risk (i.e. *CPR* < 1). Darker shading indicates periods supporting H_2 (at the 5% level) i.e. where interim Winners (Losers) have increased (decreased) second period risk (i.e. *CPR* > 1). * indicates significant at the 10% level.

Chapter 7: Exploring Tournament Behavior among Australian Superannuation Funds: A Parametric Analysis

7.1. Introduction

Chapter 6 looked for evidence of tournament behavior in Australian "multi-sector growth funds" using the non-parametric contingency table approach. In this chapter tournament induced risk-shifting behavior among this segment of Australian superannuation fund managers is further investigated using parametric analysis. Specifically, a regression-based methodology is applied to examine tournaments based on the calendar year, the financial year and an October-September year over a sample period extended to 2004. Apart from the standard tournament hypothesis the research in this chapter also explores: (a) a stability hypothesis; (b) a non-linearity hypothesis; (c) a fund age hypothesis; and (d) a fund size hypothesis.

7.2. Data and Sampling

7.2.1. Superannuation Funds

As discussed in the preceding chapter, the Australian Government's aggressive retirement provision policies are aimed at shifting the burden of funding retirement incomes from the public sector to the private sector, and superannuation has become the principal retirement savings vehicle for Australians. Consequently, superannuation funds have become the dominant component of the managed funds industry in Australia, increasing from around 65 per cent of total managed funds in 1989 to around 83 per cent in 2004.[41]

[41] Source: Reserve Bank of Australia Bulletin Statistical Tables, Table B18 Managed Funds, June 2005.

7.2.2. Data

Consistent with the research in Chapter 6, updated data were supplied by Morningstar, the independent research house which monitors the managed funds industry. The updated sample consists of monthly index series return data for the period 1989/90 to 2003/04 for retail superannuation funds classified as multi-sector growth and comprises all such funds in existence over this period. Monthly index values are calculated by reference to the month-end exit price of the fund, which is net of management fees and assumes reinvestment of all cash and bonus unit distributions. Again, a fund was included in the analysis for each full year in which it was present in the database which, as noted in Chapter 6, mitigates the survivorship bias problem created when funds which do not survive for the full sample period are absent from the database. Given the characteristics of the Australian commercial environment discussed in Chapter 6, three annual tournament scenarios: (a) Calendar year; (b) Financial (or fiscal) year and (c) September year were investigated.

As noted in the preceding chapter, managers of Multi-sector funds have discretion to invest across asset classes, and have between 60 per cent and 80 per cent of their investments allocated to growth oriented assets. Such funds therefore present a relevant environment for assessing tournament-type behavior, since managers have a reasonable degree of scope and flexibility to pursue aggressive asset allocation changes.

7.3. Research Framework

7.3.1. Definition of Core Variables

This chapter reports a number of models analyzing intra-period changes in fund risk in relation to a range of fund characteristics. As discussed in Section 6.1, the original BHS hypothesis was that fund managers who are interim losers are likely to increase fund volatility in the latter part of the assessment period to a greater extent than interim winners. This hypothesis implies a negative relationship between interim period fund performance and latter period fund risk.

As in Chapter 6, for each performance year an interim performance measure and a risk change-type variable are defined. The method of calculation follows that detailed in Section 6.3.4: with the fund's return between the commencement of the year and month M, where M ranges from the fourth month to the eighth month of the relevant year, calculated as follows:

$$RTN_{jMy} = [(1+r_{j1y})\,(1+r_{j2y})\ldots\,(1+r_{jMy})] - 1 \qquad (6.2)$$

where $r_{j1y} \ldots r_{jMy}$ are the percentage monthly change in the fund's index series value.

Once again the (relative) changes in the risk of the fund's portfolio is defined as the ratio of fund volatility before and after the interim assessment period and is captured in the 'Risk Adjustment Ratio', RAR, calculated as:

$$RAR_{jMy} = \sqrt{\left(\frac{\sum_{m=M+1}^{12}\left(r_{jmy} - \bar{r}_{j(12-M)y}\right)^2}{(12-M)-1}\right)} \div \sqrt{\left(\frac{\sum_{M=1}^{M}\left(r_{jmy} - \bar{r}_{jMy}\right)^2}{M-1}\right)} \qquad (6.3)$$

A value of RAR > 1 (= 1) [< 1] indicates that the 'end of tournament' risk for a given fund exceeds (is equal to) [is lower than] its interim period risk level.

As noted earlier, the calculation of returns and RARs is done on an annual basis. To maximize the effective sample size and explore the longer period dynamics of the tournament hypothesis. both variables are standardized by subtracting the median value of that variable for the particular year from the fund-specific observations and dividing the difference by the variable's standard deviation. This enables aggregation of the yearly results and construction of a (stacked) single series for each variable covering the full period of analysis.

7.3.2. Model and Hypothesis Development

To explore the basic relationship between interim period performance and subsequent period risk the following equation is estimated:[42]

$$RAR^{*}_{jMy} = a + bRTN^{*}_{jMy} + error_{jMy} \qquad (7.1)$$

Stated formally, the null hypothesis is that subsequent period fund risk is independent of ranking period performance. In the context of equation (7.1), we would fail to reject the null hypothesis when the estimated coefficient is equal to zero, H_0: $b = 0$.

If the null hypothesis of independence between fund performance and subsequent changes in fund risk can be rejected, the alternative hypotheses focus on examining the central prediction of the tournament hypothesis: funds with below benchmark returns in the first part of the year (losers) increase their total risk in the remaining part of the year, relative to better performing funds (winners). If this is the case it would be expected that an inverse relationship between ranking period returns and subsequent period Risk Adjustment Ratio would be found. Evidence supporting this alternative hypothesis would be provided by a slope coefficient less than zero, H_1: $b < 0$.

To explore temporal dynamics in the tournament hypothesis the sample period is divided into two sub-periods. These sub-periods are: 1989/90 – 1995/96 and 1996/97 – 2003/04 for both the September year and the Financial year tournaments and 1990-1996 and 1997-2003 for the Calendar year tournaments. This analysis is motivated by the contention that the level of competition increased dramatically across this sector of the funds management industry, between these two periods. In support of this view, attention is drawn to the numbers reported

[42] Both variables in the equation are asterisked to indicate that the standardisation process has been applied, as discussed at the end of the preceding sub-section.

in Table 6.2 – specifically, the average number of funds in the later sub-period was 84 percent, 73 percent and 95 percent greater than the average number in the earlier sub-period for the September year, Financial year and Calendar year tournaments respectively. As such, this suggests that a much different competitive dynamic might have an influence on managers' risk taking behavior. To explore for temporal dynamics a dummy variable enhanced version of equation (7.1) is employed:

$$RAR^{*}_{jMy} = a_1 + a_2 D_2 + b_1 RTN^{*}_{jMy} + b_2 (D_2 * RTN^{*}_{jMy}) + error_{jMy} \tag{7.2}$$

where $D_2 = 1$ if in second half of sample period. In this specification, b_1 represents the base case gaming coefficient – for the first half of the full sample period. The second coefficient, b_2, is the incremental gaming impact for the second sub-period relative to the first. The following hypothesesare tested: H_1: $b_1 < 0$; H_2: $b_1 + b_2 < 0$; H_3: $b_2 = 0$; H_4: $b_2 < 0$. Indeed, H_4 supports the argument that increased competitive pressure leads to a stronger incentive for managers to engage in tournament/gaming behaviour.

The basic model specified in equation (7.1) posits a linear relationship between prior period performance and subsequent period risk shifts. However, it is plausible that the relationship has a non-linear functional form, for example, because of the likely accelerated incentives for risk-shifting behaviour at the extremes of interim performance. Evidence as to the potential nonlinear relationship between performance and risk shifting may be ascertained by using a quadratic model:

$$RAR^{*}_{jMy} = a + bRTN^{*}_{jMy} + cRTN^{*\,2}_{jMy} + error_{jMy} \tag{7.3}$$

Apart from the tests of the linear term, the sign and significance of the quadratic term in this model are of interest. Logically, the quadratic term could be negative, positive or zero. A zero coefficient provides support for the base case linear model of equation (7.1). Alternatively, $c > 0$ ($c < 0$) would indicate a departure from linearity and a convex (concave) relation.

However, it's the relative magnitudes of the linear and quadratic terms that have a big bearing over whether the overall relation is a negative or positive one and whether its increasing or decreasing in strength.

Strategic interaction is further explored by combining temporal dynamics and nonlinearity to see whether there is a change in fund behavior in the more competitive second sub-period. Equation (7.4) investigates these structural features and embodies a number of testable hypotheses:

$$RAR^*_{jMy} = a_1 + a_2 D_2 + b_1 RTN^*_{jMy} + b_2 (D_2 * RTN^*_{jMy}) + c_1 RTN^{*\,2}_{jMy} + c_2 (D_2 * RTN^{*\,2}_{jMy}) + error_{jMy} \tag{7.4}$$

In this specification, b_1 (c_1) represents the base case linear (quadratic) gaming coefficient – for the first half of the full sample period. The second coefficient, b_2 (c_2), is the incremental gaming impact for the second sub-period relative to the first.

The final two models explore whether two (potentially related) fund characteristics impact upon tournament behavior: fund age and fund size. First, with regard to the age of a fund it is hypothesized that newer/younger funds have a greater incentive, and greater freedom, to chase returns than more established funds. It is likely that investors would be more strongly influenced by poor short-term performance for a fund with a short performance history than for a fund that has been around for some time. To test this hypothesis fund age is partitioned into three categories: Funds are classified as "Young" if they were in existence less than two years at the beginning of each annual tournament and as "Old" if they were in existence for more than four years at the beginning of each annual tournament. The remaining funds in the sample fall in to the middle group, namely, those in existence from two to less than four years.

The following dummy variable augmented version of equation (7.1) is used to test this hypothesis:

$$RAR^{*}_{jMy} = a_{Y} + a_{M}D_{M} + a_{O}D_{Old} + b_{Y}RTN^{*}_{jMy} + b_{M}(D_{M} * RTN^{*}_{jMy}) + b_{o}(D_{Old} * RTN^{*}_{jMy}) + error_{jMy} \quad (7.5)$$

In this specification, the coefficient b_Y represents the base case gaming coefficient – applicable to the 'young' funds in the sample. The second (third) coefficient, b_M (b_O), is the incremental gaming impact for the 'mid-age' funds ('old' funds) group relative to the 'young' funds. The formal hypotheses to be tested are as follows: H_1: $b_Y < 0$; H_2: $b_Y + b_M < 0$; H_3: $b_M = 0$; H_4: $b_Y + b_O > 0$; H_5: $b_O = 0$.

The final model tests whether fund size impacts on tournament behavior. It is plausible that the smaller the assets of a fund, the easier it is for the fund to alter its risk. Conversely, the larger the assets of a fund, the greater the implementation problems associated with changing the risk profile of the fund. Moreover, larger funds are likely to face greater scrutiny from the investment community than smaller funds, which could also act as an impediment. Accordingly, the fund sample is partitioned into three categories based upon asset size at the beginning of each annual tournament. Funds are classified as 'small' if the size of the fund falls within the bottom quartile for the tournament year. 'Big' funds are those in the top quartile and those in the remaining two quartiles are classified as 'intermediate'. Accordingly, the model to test this takes the following form:

$$RAR^{*}_{jMy} = a_{S} + a_{I}D_{I} + a_{B}D_{B} + b_{S}RTN^{*}_{jMy} + b_{I}D_{I}RTN^{*}_{jMy} + b_{B}D_{B}RTN^{*}_{jMy} + error_{jMy} \quad (7.6)$$

In this specification, the coefficient b_S represents the base case gaming coefficient – applicable to the 'small' funds in the sample. The second (third) coefficient, b_I (b_B), is the incremental gaming impact for the 'intermediate' size funds ('big' funds) group relative to the 'small' funds. The formal hypotheses relating to this model are: H_1: $b_S < 0$; H_2: $b_S + b_I < 0$; H_3: $b_I = 0$; H_4: $b_S + b_B > 0$; H_5: $b_B = 0$.

7.4. Results

7.4.1. Full Period Results

The first hypothesis is that losing managers will gamble and take on more risk in the subsequent period while winning managers will index to lock in their lead, and in doing so reduce their portfolio risk. Evidence supporting this alternative hypothesis would be provided by a negative slope coefficient. Table 7.1 reports the estimation results of Eq. (7.1).

Table 7.1 Full Period Results for the Risk Shifting-Tournament Model

Tournament (x, y)	*a*	*b*	R^2_{adj}
Panel A: September Year End			
	0.147606	-0.063003	0.0036
4,8	(8.045)**	(-3.449)**	
	0.140014	-0.069922	0.0045
5,7	(7.627)**	(-3.822)**	
	0.143276	-0.100450	0.0097
6,6	(7.849)**	(-5.512)**	
	0.114762	-0.109030	0.0116
7,5	(6.278)**	(-5.991)**	
	0.112955	-0.087710	0.0074
8,4	(6.169)**	(-4.806)**	
Panel B: Calendar Year End			
	0.201923	0.019921	0.0001
4,8	(11.683)**	(1.164)	
	0.164939	-0.034119	0.0009
5,7	(9.620)**	(-2.004)*	
	0.147075	-0.036239	0.0011
6,6	(8.556)**	(-2.118)*	
	0.05821	-0.026691	0.0004
7,5	(5.430)**	(-1.520)	
	0.077612	0.139640	0.0194
8,4	(4.507)**	(8.144)**	
Panel C: Financial Year End			
	0.177318	0.027313	0.0355
4,8	(27.447)**	(11.004)**	
	0.098681	0.023455	0.0238
5,7	(16.298)**	(8.975)**	
	0.093012	0.016553	0.0079
6,6	(12.120)**	(5.216)**	
	0.211713	0.066061	0.0085
7,5	(6.625)**	(5.384)**	
	0.535123	0.243432	0.0725
8,4	(14.470)**	(16.016)**	

This table reports the outcome of estimating the tournament risk shifting regression model:

$$RAR^{*}_{jMy} = a + bRTN^{*}_{jMy} + error_{jMy}$$

where RAR^{*}_{jMy} is the 'Risk Adjustment Ratio', which is the ratio of fund volatility before and after the interim assessment period; and RTN_{jMy} is the M-month compound return of each fund 'j', in tournament year 'y'. Each variable is, in each year, standardized by subtracting its yearly median and dividing by its yearly standard deviation. The regression is estimated using data covering the full sample period 1989 to 2004.

* statistically significant at the 5% level.

** statistically significant at the 1% level.

The September year results reported in Panel A of Table 7.1 reveal the strongest results in support of H_1, with all the slope coefficients statistically different from (less than) zero at the 1% level. These results suggest that, in the context of a September year-end tournament, losing (winning) managers appear to gamble (play it safe) and take on more (less) risk in the subsequent period. In contrast, the Financial year results reported in Panel C provide equally strong support for the hypothesis that it is winning managers who gamble and take on more risk. Here all the slope coefficients are positive and significant at the 1% level. The Calendar year results in Panel B are inconclusive: while three of the interim assessment periods reveal significant results at the 5% level or higher, two (one) of these record negative (positive) slope coefficients.

7.4.2. Sub-period Results

The apparent increase in competition in the second part of the sample period prompts us to explore whether some form of temporal dynamic exists in the tournament model. Table 7.2 presents the results for equation (7.2).

The null hypothesis is that the tournament model is maintained over the entire sample period, with no significant difference between sub-periods. Accordingly, changing parameter values between the two periods are investigated. Specifically, using equation (7.2), if the tournament model is maintained it would be expected that the slope coefficient for the second half of the sample period to be not significantly different from zero, and the combined value of the slope coefficients to be negative (in addition to the expected negativity of the base slope coefficient).

Table 7.2

Risk Shifting-Tournament Model - Subperiod Results

Tournament (x, y)	b_1	$b_1 + b_2$	b_2
Panel A: September Year-end			
4,8	-0.165047	-0.006204	0.158843
	(-5.414)**	(-0.273)	(4.178)**
5,7	-0.162186	-0.016883	0.145303
	(-5.320)**	(-0.741)	(3.818)**
6,6	-0.142187	-0.075839	0.066348
	(-4.657)**	(-3.337)**	(1.743)
7,5	-0.213493	-0.050194	0.163299
	(-7.067)**	(-2.210)*	(4.320)**
8,4	-0.159561	-0.047186	0.112375
	(5.245)**	(-2.072)*	(2.957)**
Panel B: Calendar Year-end			
4,8	-0.060935	0.061240	0.122175
	(-2.074)*	(2.914)**	(3.382)**
5,7	-0.044648	-0.028922	0.015726
	(-1.538)	(-1.376)	(0.439)
6,6	0.053027	-0.082166	-0.135193
	(1.811)	(-3.905)**	(-3.750)**
7,5	-0.001804	-0.039841	-0.038037
	(-0.060)	(-1.840)	(-1.027)
8,4	0.069317	0.175572	0.106255
	(2.353)*	(8.339)**	(2.934)**
Panel C: Financial Year-end			
4,8	0.010347	0.033108	0.022761
	(2.915)**	(8.731)**	(4.382)**
5,7	0.008883	0.035829	0.026946
	(2.404)*	(9.544)**	(5.116)**
6,6	0.014552	0.019536	0.004984
	(3.233)**	(4.200)**	(0.770)
7,5	0.006308	0.179323	0.173015
	(0.367)	(9.865)**	(6.918)**
8,4	-0.027898	0.410219	0.438117
	(-0.986)	(22.962)**	(13.095)**

This table reports the outcome of estimating the tournament risk shifting regression model:

$$RAR^*_{jMy} = a_1 + a_2 D_2 + b_1 RTN^*_{jMy} + b_2 D_2 RTN^*_{jMy} + error_{jMy}$$

where RAR^*_{jMy} is the 'Risk Adjustment Ratio', which is the ratio of fund volatility before and after the interim assessment period; and RTN_{jMy} is the M-month compound return of each fund 'j', in tournament year 'y'. Each of these variables is, in each year, standardized by subtracting its yearly median and dividing by its yearly standard deviation. The dummy variable, D_2, takes a value of unity in the second half of the sample period, defined as (a) 1996/7 to 2003/4 for the September and Financial year end tournaments and (b) 1997 to 2003 for the Calendar year tournament. The regression is estimated using data covering the period 1989 to 2004.

* statistically significant at the 5% level.
** statistically significant at the 1% level.

Panel A of Table 7.2 shows the results for the September year tournaments. Notably, the base-case slope coefficient is negative and significant at the 1 per cent level for the first sub-period, but the incremental slope coefficient in the second half of the sample period is positive and significant at the 1 per cent level in four of the five tournament periods. This finding suggests a different tournament dynamic in the second sub-period. However, the combined values of the slope coefficients remain negative in all cases and a Wald test of the combined slope coefficients reveals that they are significant in the [6,6], [7,5] and [8,4] tournament periods, indicating that although there appears to be some change in the risk shifting behavior in the second half of the period, this is not sufficient to invalidate the basic tournament model.

The Calendar year results presented in Panel B are much less clear cut: three of the incremental second period slope coefficients are significant at the 1 per cent level but two of these, for the [4,8] and the [8,4] tournaments, are positive while the coefficient for the [6,6] tournament is negative. This pattern is repeated, with significant Wald tests, for the combined slope coefficients.

The Fiscal year results reported in Panel C are, similar to Table 7.1, not supportive of the basic tournament hypothesis. The first sub-period slope coefficients for the first three tournament periods are positive and significant, as are the incremental second period slope coefficients for all but the [6,6] tournament. All of the combined slope coefficients have positive values and significant t-values for the Wald tests.

7.4.3. Exploring Non-linearities

The possibility of non-linearity in the relationship between interim period ranking and subsequent risk-shifting behavior was explored using the quadratic model specified in equation (7.3). Before going on to consider the outcome of these estimations it is worth briefly diverting attention to how the possible cases emanating from this quadratic specification could be meaningfully characterized. The first thing to note is that both key variables have been standardized such that the slope coefficient tells us what happens to RAR for a one standard deviation change in RTN, away from the median. Thus, it can confidently be assumed that the relevant range of RTN* over which to consider our model's estimates is (-3, +3) ie -/+ 3 standard deviations away from the median. By definition, the vast mass of observations will be captured in this range. Over this range, it is possible to characterize six distinct cases and these cases are depicted in Figure 7.1, while Figure 7.2 provides a summary of the conditions leading to each characterized case.

Figure 7.1 Characterisation of Quadratic Tournament Model

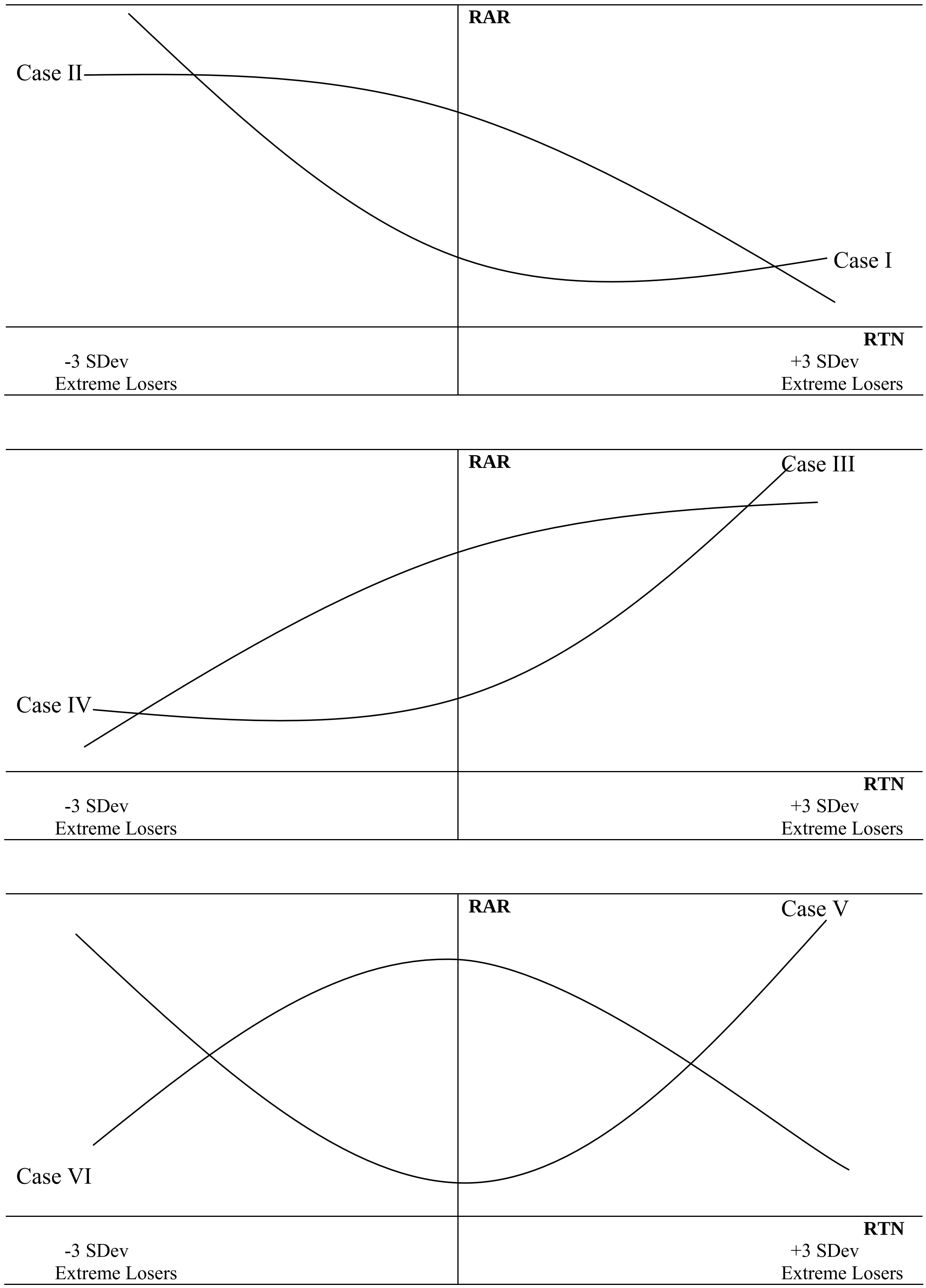


Figure 7.2 Summary of Conditions Leading to Characterised Cases in the Quadratic Model

This figure sets out a summary of the conditions under which the six characterized cases depicted in Figure 7.1 will take place in the context of the quadratic model:

$$RAR^{*}_{jMy} = a + bRTN^{*}_{jMy} + cRTN^{*\ 2}_{jMy} + error_{jMy}$$

Panel A: Coefficient Conditions to Produce Characterised Cases				
	$b > 0$		$b < 0$	
	$\|b\| >> \|c\|^{*}$	$\|b\| << \|c\|^{**}$	$\|b\| >> \|c\|^{*}$	$\|b\| << \|c\|^{**}$
$c > 0$	Case III	Case V	Case I	Case V
$c < 0$	Case IV	Case VI	Case II	Case VI

Panel B: Summary Description of each Characterised Case		
	Extreme Losers	Extreme Winners
Case I	Increasingly chasing high risk	Decreasingly chasing low risk
Case II	Decreasingly chasing high risk	Increasingly chasing low risk
Case III	Decreasingly chasing low risk	Increasingly chasing high risk
Case IV	Increasingly chasing low risk	Decreasingly chasing high risk
Case V	Increasingly chasing high risk	Increasingly chasing high risk
Case VI	Increasingly chasing low risk	Increasingly chasing low risk

[*] This represents the situation in which the magnitude of the linear term (*b*) dominates the magnitude of the quadratic term (*c*).
[**] This represents the situation in which the magnitude of the linear term (*b*) dominates the magnitude of the quadratic term (*c*).

From these figures the following can be seen. First, Case I shows a convex relation between RAR and RTN, which occurs when $b < 0$ and $c > 0$, with the magnitude of the former substantially exceeding the magnitude of the latter. This circumstance reflects a scenario in which extreme losers (winners) are increasingly (decreasingly) chasing high (low) risk. Second, Case II shows a concave relation between RAR and RTN, which occurs when $b < 0$ and $c < 0$, with the magnitude of the former substantially exceeding the magnitude of the latter. This circumstance reflects a scenario in which extreme losers (winners) are decreasingly (increasingly) chasing high (low) risk.

Third, Case III shows a convex relation between RAR and RTN, which occurs when $b > 0$ and $c > 0$, with the magnitude of the former substantially exceeding the magnitude of the latter. This circumstance reflects a scenario in which extreme losers (winners) are decreasingly (increasingly) chasing low (high) risk. Fourth, Case IV shows a concave relation between RAR and RTN, which occurs when $b > 0$ and $c < 0$, with the magnitude of the former substantially exceeding the magnitude of the latter. This circumstance reflects a scenario in which extreme losers (winners) are increasingly (decreasingly) chasing low (high) risk.

Fifth, Case V shows a convex relation between RAR and RTN, which occurs for *b* of either sign and $c > 0$, with the magnitude of the latter substantially exceeding the magnitude of the former. This circumstance reflects a scenario in which extreme losers and extreme winners are both increasingly chasing high risk. Sixth, Case VI shows a concave relation between RAR and RTN, which occurs for *b* of either sign and $c < 0$, with the magnitude of the latter substantially exceeding the magnitude of the former. This circumstance reflects a scenario in which extreme losers and extreme winners are both increasingly chasing low risk.

The estimated regression results are presented in Table 7.5. The September year results (Panel A) reveal little evidence of non-linearity: the slope coefficients for all tournament periods are significant and less than zero, but only one of the quadratic terms has a significant coefficient. Specifically, tournament [5,7] conforms to characterization, case I: the magnitude of the negatively signed linear term (-0.07), substantially exceeds the magnitude of the positively signed quadratic term (0.0195). As pointed out in Figure 7.2, this represents a case in which extreme losers increasingly chase high risk, while extreme winners decreasingly chase low risk.

The Financial year results presented in Panel C display linear coefficients that are positive and significant across all tournament periods. However, there is also some evidence of non-linearity with the [5,7] and [6,6] tournament periods showing positive and significant coefficients on the quadratic term. As such, these two tournaments conform to the Case III characterization since the magnitude of the positively signed linear term, substantially exceed the magnitude of the positively signed quadratic term. This represents a case in which extreme losers decreasingly chase low risk, while extreme winners increasingly chase high risk. However, the coefficient on the quadratic term for the [8,4] period while significant, is negative – thereby conforming to Case IV. Hence, here extreme losers increasingly chase low risk, while extreme winners decreasingly chase high risk.

It is difficult to draw any consistent inferences from the results for the Calendar year regressions. Three of the linear term coefficients are significant but the [5,7] and]6,6] periods have negative coefficients, while the [8,4] period has a positive coefficient. The quadratic term for this latter tournament is also significant, but is negative in sign. Hence, it is very similar to its counterpart in Panel C, conforming to Case IV. The only other significant quadratic coefficient is for the [4,8] period where it has a positive value. However, the slope coefficient for this period is not significant. This is a Case V situation: one in which both extreme losers and extreme winners increasingly chase high risk.

The issue of non-linearity was also explored further through equation (7.4) which investigates non-linearity in the two sub-periods identified earlier. The quadratic function employed (as in equation 7.3) is the standard approximating function to any differential non-linear function. It is a second order Taylor Series Expansion, widely used in econometric research to test for non-linearity.

Equations 7.4 through 7.6 use dummy variables to test for temporal stability, age and size effects, respectively. This also is a well established and widely used technique in finance research.

Table 7.3 Non-linear Risk Shifting-Tournament Model - Subperiod Results

Tournament (x, y)	b_1	$b_1 + b_2$	b_2	c_1	$c_1 + c_2$	c_2
Panel A: September Year End						
4,8	-0.161199	-0.007952	0.153248	0.007015	0.003027	-0.003988
	(-5.154)**	(-0.345)	(3.945)**	(0.554)	(0.463)	(-0.280)
5,7	-0.140673	-0.020810	0.119863	0.034060	0.009172	-0.024888
	(-4.481)**	(-0.906)	(3.082)**	(2.816)**	(1.253)	(-1.760)
6,6	-0.127500	-0.073431	0.054070	0.028913	-0.007525	-0.036438
	(-4.113)**	(-3.212)**	(1.404)	(2.656)**	(-0.894)	(-2.648)**
7,5	-0.209675	-0.049406	0.160269	0.027637	-0.002227	-0.029864
	(-6.936)**	(-2.161)*	(4.229)**	(2.505)*	(-0.288)	(-2.216)**
8,4	-0.142033	-0.046261	0.095772	0.040604	-0.003982	-0.044586
	(-4.612)**	(-2.029)*	(2.499)*	(3.438)**	(-0.524)	(-3.175)**
Panel B: Calendar Year End						
4,8	-0.059532	0.053398	0.112930	-0.002847	0.045604	0.048451
	(-2.003)*	(2.537)*	(3.100)**	(-0.283)	(4.191)**	(3.271)**
5,7	-0.045520	-0.029106	0.016413	0.004445	-0.002876	-0.007322
	(-1.563)	(-1.383)	(0.457)	(0.419)	(-0.253)	(-0.470)
6,6	0.042024	-0.080089	-0.122114	-0.020184	0.017199	0.037382
	(1.417)	(-3.798)**	(-3.355)**	(-2.248)*	(1.309)	(2.349)*
7,5	-0.034574	-0.031668	0.002906	-0.029883	0.044336	0.074219
	(-1.096)	(1.458)	(0.076)	(-3.325)**	(3.287)**	(4.579)**
8,4	0.031147	0.173477	0.142330	-0.031453	-0.016268	0.015185
	(1.000)	(8.231)**	(3.785)**	(-3.711)**	(1.277)	(0.992)
Panel C: Financial Year End						
4,8	0.016188	-0.028122	-0.044310	0.003938	-0.013485	-0.017423
	(4.235)**	(-2.222)*	(-3.352)**	(3.973)**	(-5.068)**	(-6.136)**
5,7	0.020427	0.043365	0.022937	0.003974	0.002031	-0.001943
	(4.009)**	(4.131)**	(1.966)*	(3.285)**	(0.769)	(-0.669)
6,6	0.020193	0.090770	0.070577	0.002422	0.016244	0.013823
	(3.665)**	(6.341)**	(4.601)**	(1.760)	(5.259)**	(4.087)**
7,5	0.009452	1.131073	1.121622	0.001510	0.175640	0.174131
	(0.491)	(18.051)**	(17.109)**	(0.319)	(15.821)**	(14.430)**
8,4	0.003870	0.562095	0.558225	0.017106	0.028713	0.011607
	(0.124)	(10.831)**	(9.208)**	(2.336)*	(3.116)**	(0.986)

This table reports the outcome of estimating the quadratic tournament risk shifting regression model:
$RAR^*_{jMy} = a_1 + a_2 D_2 + b_1 RTN^*_{jMy} + b_2 D_2 RTN^*_{jMy} + c_1 (RTN^*_{jMy})^2 + c_2 D_2 (RTN^*_{jMy})^2 + error_{jMy}$ where RAR^*_{jMy} is the 'Risk Adjustment Ratio', which is the ratio of fund volatility before and after the interim assessment period; and RTN_{jMy} is the M-month compound return of each fund 'j', in tournament year 'y'. Each of these variables is, in each year, standardized by subtracting its yearly median and dividing by its yearly standard deviation. The dummy variable, D_2, takes a value of unity in the second half of the sample period, defined as (a) 1996/7 to 2003/4 for the September and Financial year end tournaments and (b) 1997 to 2003 for the Calendar year tournament. The regression is estimated using data covering the period 1989 to 2004.

* statistically significant at the 5% level.
** statistically significant at the 1% level.

The results of this analysis, which appear in Table 7.3, are interesting. Initially, consider the September Year results in Panel A. First, we see that for the first sub-period the base case, linear (b_1) and quadratic (c_1) coefficients are negative and positive, respectively (significant at the one per cent level).[43] As such, given that the magnitude of the former are larger than the latter, these results conform to Case I: extreme losers increasingly chase high risk, while extreme winners decreasingly chase low risk. This is similar to the overall results for September (Table 7.3). Next, we see that with regard to the second sub-period there are some differences relative to the base case. In all instances (except [6,6]) the incremental linear terms are positive and statistically significant. Overall however, the latter three tournaments still show a significantly negative linear term ($b_1 + b_2$). Turning to the quadratic terms in the second sub-period we see that the non-linearity evident in sub-period 1 is no longer apparent – the incremental coefficient (c_2) is significantly negative in four cases, thereby leading to an overall insignificance.

Next consider the Calendar Year results presented in Panel B of Table 7.3. It is evident that the first sub-period mostly conforms to Case VI: specifically, for Tournaments [6,6]; [7,5] and [8,4] the quadratic term is significantly negative and it dominates the linear term (which is always insignificant). As such, extreme losers and extreme winners both increasingly chase low risk. Once again the evidence of non-linearity in the second sub-period is weaker. Indeed, only [4,8] and [7,5] suggest significant quadratic terms ($c_1 + c_2$), and when considered together with their linear counterparts ($b_1 + b_2$) indicate that Case V is applicable. That is, extreme losers and extreme winners both increasingly chase high risk

Finally with regard to Table 7.3, the Financial year results are presented in Panel C. Here there is one major observation to document: it is evident that Case III is most prevalent – across both sub-periods. Specifically, while the quadratic term is often significantly positive, it is dominated in magnitude terms by a significantly positive linear term: this is true for Tournaments [4,8]; [5,7] and [6,6] in the first sub-period and for Tournaments [6,6]; [7,5]

[43] Tournament (4,8) is the one exception, wherein the quadratic coefficient is insignificant.

and [8,4] in the latter sub-period. As such, extreme losers decreasingly chase low risk, while extreme winners increasingly chase high risk.

The fund age hypothesis was examined through equation (7.5) and the results appear in Table 7.4. As noted earlier, funds are classified as “Young” (“Old”) if they were in existence less than two (more than four) years at the beginning of each annual tournament. Panel A of Table 7.4 indicates that there is little difference in behaviour across funds partitioned on age. Specifically, both young and old funds display a significantly inverse relation between interim performance and subsequent period risk adjustment.

Table 7.4 Risk Shifting-Tournament Model – Conditioned by Fund Age

Tournament (x, y)	b_y	$b_y + b_M$	b_M	$b_Y + b_O$	b_O	R_{adj}^2
Panel A: September Year End						
4,8	-0.088419	-0.014235	0.074185	-0.064947	0.023473	0.0040
	(-2.423)*	(-0.332)	(1.318)	(-2.670)**	(0.535)	
5,7	-0.002669	-0.059152	-0.056483	-0.098062	-0.096393	0.0089
	(-0.072)	(-1.351)	(-0.987)	(-4.091)**	(-2.168)*	
6,6	-0.081465	-0.056638	0.024827	-0.115789	-0.034324	0.0119
	(-2.214)*	(-1.288)	(0.433)	(-4.844)**	(-0.782)	
7,5	-0.120927	-0.089606	0.031321	-0.104320	0.016607	0.0122
	(-3.261)**	(-2.095)*	(0.553)	(-4.336)**	(0.376)	
8,4	-0.095496	-0.073041	0.022455	-0.081106	0.014391	0.0095
	(-2.614)*	(-1.677)	(0.395)	(-3.358)**	(0.329)	
Panel B: Calendar Year End						
4,8	0.111517	0.068041	-0.043476	-0.027690	-0.139207	0.0087
	(3.091)**	(1.854)	(-0.845)	(-1.213)	(-3.260)**	
5,7	0.095044	-0.029296	-0.124340	-0.086054	-0.181097	0.0084
	(2.712)**	(-0.7891)	(-2.436)*	(-3.7743)**	(-4.332)**	
6,6	0.087049	-0.034537	-0.121586	-0.081671	-0.168720	0.0099
	(2.469)*	(-0.905)	(-2.341)*	(-3.598)**	(-4.023)**	
7,5	0.159186	0.002818	-0.156369	-0.110797	-0.269984	0.0164
	(4.355)**	(0.075)	(-2.979)**	(-4.738)**	(-6.222)**	
8,4	0.228525	0.221860	-0.006665	0.076437	-0.152088	0.0355
	(6.351)**	(5.994)**	(-0.129)	(3.378)**	(-3.578)**	
Panel C: Financial Year End						
4,8	0.032606	0.020433	-0.012173	0.028534	-0.004072	0.0354
	(6.002)**	(4.039)**	(-1.640)	(8.457)**	(-0.637)	
5,7	0.033722	0.019520	-0.014202	0.020869	-0.012853	0.0244
	(5.887)**	(3.480)**	(-1.771)	(6.030)**	(-1.920)	
6,6	0.020904	0.018164	-0.002740	0.014101	-0.006802	0.0075
	(3.063)**	(2.690)**	(-0.285)	(3.321)**	(-0.846)	
7,5	0.048706	0.098139	0.049433	0.060721	0.012015	0.0079
	(1.829)*	(3.531)**	(1.284)	(3.787)**	(0.387)	
8,4	0.258963	0.214554	-0.044409	0.244474	-0.014489	0.0719
	(7.870)**	(5.802)**	(-0.897)	(12.567)**	(-0.379)	

This table reports the outcome of estimating the tournament risk shifting regression model:

$$RAR^*_{jMy} = a_Y + a_M D_M + a_O D_{Old} + b_Y RTN^*_{jMy} + b_M D_M RTN^*_{jMy} + b_o D_{Old} RTN^*_{jMy} + error_{jMy}$$

where RAR^*_{jMy} is the 'Risk Adjustment Ratio', which is the ratio of fund volatility before and after the interim assessment period; and RTN_{jMy} is the M-month compound return of each fund 'j', in tournament year 'y'. Each of these variables is, in each year, standardized by subtracting its yearly median and dividing by its yearly standard deviation. The dummy variable, D_M (D_{Old}), takes a value of unity if the fund is 'mid-aged' ('old') defined as being 2-4 years (> 4 years) at the beginning of the given tournament. The regression is estimated using data covering the period 1989 to 2004.

* statistically significant at the 5% level.** statistically significant at the 1% level.

The Calendar year results, reported in Panel B, present a quite different picture. In each tournament period the slope coefficient for the young funds is positive and significant while the counterpart slope coefficient for the old funds is significantly lower (that is, the incremental coefficient is significantly negative). Wald tests on the combined slope coefficients are significant for all but the [4,8] tournament period. The combined slope coefficients are negative for the [5,7], [6,6] and [7,5] periods but positive for the [8,4] period. This indicates that generally it is the behavior of the more established funds that is driving the tournament effect, while contrary to predictions younger funds tend to chase higher risk, the better has been their interim performance. This may reflect a degree of 'hubris' on the part of managers of new/young funds.

The Financial Year results (Panel C), similar to their Panel A counterparts, reveal that there is little difference in behaviour across funds partitioned on age. However, in contrast to the Panel A results, here in the case of the Financial Year analysis all three categories of funds display a significantly positive relation between interim performance and subsequent period risk adjustment. This finding suggests that regardless of fund age, all funds tend to ramp up risk on the back of good interim performance.

Finally, the impact of fund size on risk shifting behavior is examined, and these results are reported in Table 7.8. In Panel A, we observe that for the September Year tournaments the risk shifting tournament behaviour seems to be mostly driven by mid-sized funds: these funds generally exhibit the predicted negative relation, while neither the small nor the large fund groupings shown any evidence (positive or negative) of a link between *RAR* and *RTN*. In Panel B, the Calendar Year results indicate that regardless of fund size, there is little evidence of risk shifting behaviour at all. Finally, in Panel C of Table 7.8 the Financial Year show a different picture. At a general level, there is a strong tendency regardless of fund size toward positive risk shifting. However, it is interesting to note that for the [7,5] and [8,4] tournaments there is some suggestion that this tendency is less strong for both the intermediate and large funds (as reflected by their significantly negative incremental slope coefficients).

Table 7.5 Risk Shifting-Tournament Model – Conditioned by Fund Size

Tournament (x, y)	b_S	$b_S + b_I$	b_I	$b_S + b_B$
Panel A: September Year End				
4,8	-0.007494	-0.014739	-0.007245	-0.007280
	(-2.203)*	(-0.388)	(-0.137)	(-0.117)
5,7	0.057783	-0.033456	-0.091239	-0.080821
	(1.550)	(-0.882)	(-1.716)*	(-1.333)
6,6	0.002607	-0.144114	-0.146722	-0.119791
	(0.072)	(-3.739)**	(-2.770)**	(-1.953)
7,5	0.040082	-0.158472	-0.198554	-0.109624
	(1.092)	(-4.224)**	(-3.783)**	(-1.726)
8,4	0.045360	-0.128143	-0.173503	-0.103710
	(1.203)	(-3.418)**	(-3.263)**	(-1.735)
Panel B: Calendar Year End				
4,8	0.111154	0.001073	-0.110081	0.069760
	(3.156)	(0.032)	(-2.260)*	(1.181)
5,7	-0.018522	-0.051057	-0.032534	0.044173
	(-0.534)	(-1.524)	(-0.675)	(0.756)
6,6	-0.006012	-0.051687	-0.045675	-0.049335
	(-0.173)	(-1.502)	(-0.934)	(-0.902)
7,5	0.107075	-0.044099	-0.157174	-0.055045
	(2.934)**	(-1.239)	(-2.965)**	(-0.961)
8,4	0.136917	0.030376	-0.106541	0.120809
	(3.822)**	(0.880)	(-2.142)*	(2.242)*
Panel C: Financial Year End				
4,8	0.038145	0.024764	-0.013381	0.030566
	(8.197)**	(6.454)**	(-2.219)*	(5.757)**
5,7	0.023028	0.014782	-0.008247	0.017089
	(5.175)**	(3.671)**	(-1.374)	(3.048)**
6,6	0.006357	-0.013330	-0.019687	-0.008581
	(0.938)	(-2.197)*	(-2.164)*	(-1.014)
7,5	0.105587	-0.023806	-0.129393	-0.009754
	(3.369)**	(-0.865)	(-3.102)**	(-0.255)
8,4	0.359693	0.272853	-0.086840	0.251114
	(12.122)**	(10.666)**	(-2.217)*	(7.060)**

This table reports the outcome of estimating the tournament risk shifting regression model:

$$RAR^*_{jMy} = a_S + a_I D_I + a_B D_B + b_S RTN^*_{jMy} + b_I D_I RTN^*_{jMy} + b_B D_B RTN^*_{jMy} + error_{jMy}$$

where RAR^*_{jMy} is the 'Risk Adjustment Ratio', which is the ratio of fund volatility before and after the interim assessment period; and RTN_{jMy} is the M-month compound return of each fund 'j', in tournament year 'y'. Each of these variables is, in each year, standardized by subtracting its yearly median and dividing by its yearly standard deviation. The dummy variable, D_I (D_B), takes a value of unity if the fund is 'intermediate sized' ('big) defined as being in the two middles size quartiles (top size quartile) at the beginning of the given tournament. The regression is estimated using data covering the period 1989 to 2004.

7.5. Summary and Conclusion

This chapter investigated the tournament induced risk-shifting behavior of Australian "multi-sector growth funds", using a sample period covering 1989 to 2004. In contrast to Chapter 6, a regression-based methodology was applied and tournaments based on the calendar year, the financial year and an October-September year were examined, using a range of within-year assessment periods. Apart from the standard tournament hypothesis the following related hypotheses were explored: (a) a stability hypothesis; (b) a non-linearity hypothesis; (c) a fund age hypothesis; and (d) a fund size hypothesis.

The findings can be summarized as follows. First, at the broadest level evidence is found in favour of the risk shifting tournament hypothesis when tournaments are defined with a September year end. In contrast, risk shifting of an opposite nature is found for financial year end tournaments – that is, good (poor) interim performers tend to increase (decrease) risk. This latter finding may be a reflection of evidence in favour of the Taylor (2002) 'active competition' hypothesis. Second, The sub-period investigation revealed a strong pattern of less negative (more positive) association between interim performance and risk shifting for the September-based (Financial year) tournaments. This is consistent with the argument that the latter half of the sample has become more crowded with funds and, hence, more competitive. Thus, the findings may again be a reflection of the Taylor 'active competition' hypothesis.

Third, the investigation of potential non-linearities revealed a mixture of findings. On the one hand, September year end tournaments tend to be typified by 'Case I': namely, a convex relation between RAR and RTN in which extreme losers increasingly chase high risk, while extreme winners decreasingly chase low risk. Interestingly this behaviour seems most evident in our first sub-period and disappears in the second sub-period – in the latter it reverts to a linear risk shifting phenomenon. It is possible that the increased competition in the second sub-period has helped bring about this change. On the other hand, Financial year end tournaments tend to be typified by 'Case III': namely, a convex relation between RAR and RTN, reflecting a scenario in which extreme losers (winners) are decreasingly (increasingly) chasing low (high) risk. Notably, this phenomenon seems more stable across the two sub-periods.

Fourth, the analysis of a 'fund age' hypothesis produced results that age doesn't matter in either the September or Financial year end tournament scenarios. However, in the case of

Calendar years the conventional tournament effect seems to be coming from the more established funds. In contrast, younger funds tend to chase higher risk, the better has been their interim performance – possibly reflecting ‘hubris’ on the part of these managers.

Finally, the ‘fund size’ hypothesis for (a) the September year tournaments suggests that, if anything, it is intermediate sized funds pursuing risk shifting tournament; (b) the Calendar year there is little evidence of risk shifting behaviour, regardless of fund size; (c) the Financial year there is a general tendency, regardless of fund size, toward positive risk shifting.

Chapter 8: Conclusion

8.1. Introduction

The investment management industry has proven to be fertile ground for theoretical and empirical research over the past forty years, particularly in relation to the nature and quantification of risk. However, as noted in Chapter 1, the dominance of the U.S. industry has meant that much of the academic research has focused on the U.S. market. This thesis investigates aspects of investment risk using alternative data to that used in much of the prior published. As such, it represents a serious contribution towards redressing the imbalance.

This thesis contains an extensive analysis of aspects of risk related to both the demand side and the supply side of the managed funds market in Australia. Among the demand side characteristics, attitudes towards risk and their impact on asset allocation decisions will be an important determinant of investors' financial well-being, particularly in retirement. Accordingly, Chapters 2 to 4 examine the financial risk tolerance of investors. These chapters explore the relationship between subjective financial risk tolerance and a range of demographic characteristics that are widely used as a basis for heuristically derived estimates of investors' attitudes towards financial risk.

The analysis of the supply side of the industry focuses on risk-shifting behavior by investment fund managers. Since the performance and risk-shifting behavior of fund managers was initially put under the spotlight by Treynor and Mazuy (1966) and Jensen (1968), it is possible to identify an evolving strand in the research where performance assessment is examined within the framework of the principal-agent literature. One focus that has emerged in this literature is the adaption by Brown et al. (1996) of the tournament model to the analysis of investment manager behavior, wherein it is hypothesized that fund managers who were interim losers were likely to increase fund volatility in the latter part of the assessment period to a greater extent than interim winners.

Against this background, Chapters 5 to 7 examine risk-shifting behavior by Australian fund managers. Chapter 5 investigates the ability of fund managers to time the market while Chapters 6 and 7 explore the applicability of the tournament model of funds management to a segment of the Australian industry.

The purpose of this final chapter is to provide an overview of the analysis and present the overall conclusions of the thesis. Additionally, it discusses the contributions, identifies its limitations and considers possible directions for future research.

8.2. Overview and Conclusions

The analysis in chapters 2 to 5 draws upon a database that contains a psychometrically derived risk tolerance score (RTS) plus responses to eight demographic questions. Chapter 2 contains an exploratory analysis of a sample of 3214 Australian respondents. The focus of this study is an examination of the relationship between subjective risk tolerance and demographic factors for a sample group considered representative of those individuals likely to be active investors. The analysis provides insight into the effect of certain demographic characteristics on individuals' attitudes towards risk and provides evidence supportive of the validity of widely used demographics such as gender, age, income and wealth as determinants of risk tolerance. However, the relationships found are not as simple as implied by the demographic heuristics: Risk tolerance exhibits a concave relationship with income across all age groups, and irrespective of gender. Moreover, education, marital status and dependents, which have been found to be significant in previous studies, were not found to be significant determinants of an individual's attitude towards risk in this study.

Chapter 3 continues the investigation of the relationship between demographic factors and financial risk tolerance. In this study the sample size ranges between 16461 and 20415 depending upon which demographic characteristic is being examined. While it is found that peoples self-assessed risk tolerance and FinaMetrica RTS generally accord, there is considerable variation with a tendency for respondents to under-estimate their risk tolerance. The analysis of the relationship between participant demographics and risk tolerance reveals that gender, age, income and wealth are significantly associated with financial risk tolerance, results consistent with the analysis in Chapter 2. A detailed investigation of the relationship between risk tolerance and age as well as marital status was also performed. The results suggest that a negative relationship between age and risk tolerance exists which, while in line with generally held industry beliefs, contradicts some of the more recent research findings. Further, it was found that the relationship between age and risk tolerance exhibits a significant nonlinear structure. In contrast to the findings of the exploratory study in Chapter 2, a trade/diploma level of education or higher, marital status and the number of dependents were all found to be significant determinents of an individual's attitude towards risk. The relationship between marital status and risk tolerance was found to be negative. However, while the number of dependents was found to be significantly associated with RTS for our sample group, the negative impact on RTS is small in magnitude.

Chapter 4 extends the analysis of Chapter 3, with particular focus on the issue of whether women differ from men in their attitude to financial risk taking. Consistent with the results of the study in Chapter 3, regression analysis of risk tolerance scores (RTS) on the demographic characteristics of gender, marital status, number of dependents, age, education, income, combined income and net assets revealed each of these characteristics to be significant at the 1% level, with the first four characteristics having a negative relationship with RTS. The impact of gender was explored through dummy variable enhanced regression analysis constructed to test the increment in each demographic coefficient derived from being female relative to the base case of being male. While it was found the fixed component of the RTS to be 9.6 points lower for females, the magnitude of this impact is reduced once the other demographic characteristics are taken into account. Marriage and number of dependents were found to be differentially important characteristics, with marriage having a less negative impact on risk tolerance for females than the negative impact found for males. Age reduces risk tolerance by 3.39 points per decade for males, and its differential impact for females is positive but negligible, being associated with a decrease of 2.91 points per decade (i.e. 0.48 points lower in magnitude).

On the other hand, the combined income effect derived from marriage and the level of net assets of the respondent, which have positive impacts per category for males, have correspondingly incremental negative impacts for females. Education was not found to be a significant differentiating variable in explaining the RTS of females. While important for both males and females in the sense that it is associated with an increase in RTS per education category, the results show that no more or less importance is attached to it by females. Finally, evidence was found of nonlinear effects in the relationship between RTS and the number of dependents, age and income and combined income.

Chapter 5 moves the focus to the supply side of the investment market, and focuses on the identification of market timing ability on the part of fund managers. Using both quadratic excess returns market model and dual-beta excess returns market model regressions, the results suggested that for the sample over the period examined, there is little evidence of market timing ability. Further, there is no clear dominance of one market timing model over the other. It was found, however, that a cubic market model specification does fit the data quite well for nearly one third of the sample.

Chapter 6 investigates whether there is evidence of tournament induced risk-shifting behavior among managers of Australian “multi-sector growth funds” over a sample period covering 1989 to 2001. Following Taylor (2003), the study tests the ability of the two competing hypotheses to predict risk-shifting behavior in the sample. To this end, a non-parametric Cross-Product Ratio methodology is used to examine tournaments based on the calendar year, the financial year and an October-September year, using a range of within-year assessment periods, against both an exogenous and an endogenous benchmark.

The findings can be summarized as follows. At a broad level the research finds evidence in support of Taylor’s model. Specifically, when an exogenous benchmark is used (i.e. market index return), support is uncovered for the hypothesis that losing managers at the end of the interim assessment period increase the risk of the fund in the subsequent period, while winning managers reduce their risk (H_1). This support is particularly evident for the Calendar-year analysis. However, the volatility underlying this finding warrants a careful qualification to any conclusion that can be drawn from this analysis. In particular, the extent to which this gaming behavior occurs (for Calendar/index benchmark tournaments), either (a) it is a more long-term in nature or (b) it is largely a recent phenomenon (with no guarantee of continuation). Either way, given the limited evidence to date, it will be difficult to predict over any short-term horizon.

The second hypothesis (H_2) which comes from the Taylor (2003) model, is that assessment against an endogenous benchmark, such as a median fund performance, will induce winning (losing) managers to take on more (less) risk in the subsequent period. Viewed as a whole, the analysis involving endogenous benchmarks is also quite supportive of H_2. This is particularly so for the Financial-year investigations (and to a lesser extent also with the Calendar-year results). Once again, this is consistent with the view that the Australian financial press and investors are particularly fixated on Financial and Calendar-year investment performance.

The final empirical chapter of this thesis extends the analysis of Chapter 6 and applies a regression-based methodology to investigate the tournament induced risk-shifting behavior of Australian “multi-sector growth funds” over the period 1988 to 2004. Tournaments based on the calendar year, the financial year and an October-September year are investigated, using a range of within-year assessment periods. Apart from the standard tournament hypothesis the study also explores: (a) a stability hypothesis; (b) a non-linearity hypothesis; (c) a fund age hypothesis; and (d) a fund size hypothesis.

The findings in Chapter 7 can be summarized as follows. First, at the broadest level there is evidence in favour of the risk shifting tournament hypothesis when tournaments are defined with a September year end. In contrast, the study finds risk shifting of an opposite nature for financial year end tournaments – that is, good (poor) interim performers tend to increase (decrease) risk. This latter finding may be a reflection of evidence in favour of the Taylor (2002) ‘active competition’ hypothesis. Second, the sub-period investigation revealed a strong pattern of less negative (more positive) association between interim performance and risk shifting for the September-based (Financial year) tournaments. The argument was that the latter half of our sample has become more crowded with funds and, hence, more competitive. Thus, the findings may again be a reflection of the Taylor ‘active competition’ hypothesis.

Third, the investigation of potential non-linearities revealed a mixture of findings. On the one hand, September year end tournaments tend to be typified by ‘Case I’: namely, a convex relation between RAR and RTN in which extreme losers increasingly chase high risk, while extreme winners decreasingly chase low risk. Interestingly this behaviour seems most evident in the first sub-period and disappears in the second sub-period – in the latter it reverts to a linear risk shifting phenomenon. It is possible that the increased competition in the second sub-period has helped bring about this change. On the other hand, Financial year end tournaments tend to be typified by 'Case III': namely, a convex relation between RAR and RTN, reflecting a scenario in which extreme losers (winners) are decreasingly (increasingly) chasing low (high) risk. Notably, this phenomenon seems more stable across the two sub-periods.

Fourth, the analysis of a 'fund age' hypothesis produced results that age doesn't matter in either the September or Financial year end tournament scenarios. However, in the case of Calendar years the conventional tournament effect seems to be coming from the more established funds. In contrast, younger funds tend to chase higher risk, the better has been their interim performance – possibly reflecting 'hubris' on the part of these managers.

Finally, the 'fund size' hypothesis for (a) the September year tournaments suggests that, if anything, it is intermediate sized funds pursuing risk shifting tournament; (b) the Calendar year there is little evidence of risk shifting behaviour, regardless of fund size; (c) the Financial year there is a general tendency, regardless of fund size, toward positive risk shifting.

8.3. Contribution

The key contributions of this thesis can be classified into two main areas, both dealing with aspects of risk in the investment market. First, the thesis examines the relationship between subjective risk tolerance and a range of demographic characteristics that are widely used as a basis for heuristically derived estimates of investors' attitudes towards financial risk. The thesis departs from previous research in the area by using a very large sample of psychometrically derived risk tolerance scores. The examination of a large Australian database also provides a response to the observation made by Jiankoplos and Bernasek (1998) that most of the risk tolerance research uses United States data and consequently the results could be country specific.

The analysis of financial risk tolerance produces a number of findings having practical import for the financial services industry. The finding in Chapter 2 that the relationship between risk tolerance and income is concave across all age groups refines the understanding of the relationship between risk tolerance and this commonly used heuristic and serves as a caution against ready acceptance of the widely held belief that there is a simple positive relationship between the two variables. Similarly, the finding in Chapter 3 that there is a tendency for respondents to under-estimate their risk tolerance suggests that financial planners who rely largely on subjective assessments of risk tolerance run the risk of suggesting inappropriate, and in the majority of cases overly conservative, investment strategies for their clients. In a similar vein, the finding that a trade/diploma level of education is necessary before education becomes a significant determinent of risk tolerance deepens our understanding of the relationship between risk tolerance and this heuristic.

Assessment of an investor's risk profile is a highly influential factor in the construction of an appropriate investment portfolio. The research contained in Chapter 4, in providing support for the widely held view that women have lower risk tolerance than men and that, at least in a cross-sectional sense, age has an inverse, though non-linear, relationship with risk tolerance, has important implications for the funds management industry: as the baby boomer cohort ages and moves into retirement we could expect to see demand shift away from the relatively more risky growth asset classes towards the less risky income asset classes, reflecting the decline in risk tolerance associated which increasing age. Moreover, this effect would be compounded by the greater life expectancy of women: as the population ages the gender composition will shift in favor of women, who on average have lower risk tolerance. Thus, the findings in Chapter 4, coupled with the changing age and gender demographics of the population, suggests there will be a duel force for change in the composition of the overall demand for investment products. Accordingly, and in the context of an aging and increasingly female world the key implications of the findings in Chapter 4 are most apparent in the managed funds industry over a medium to longer term timeframe (looking at 2030 and beyond): as the baby boomer bulge moves through the age profile, the gender composition will shift further in favor of women. To the extent that women do have more conservative risk profiles and the extent to which this conservatism is exacerbated with age, we could expect to see asset allocation decisions leading to an overall shift to less risky investment portfolios. Importantly, the existence of a positive equity premium means that such a shift in overall asset allocation has the potential to lead to lower levels of wealth for women in their retirement years. At a macro level, in the absence of countervailing forces at play, it may lead to lower levels of 'speculative' capital being available for venture capital and other extreme risk projects that currently attract funding.

The second area where the thesis makes a significant contribution is in relation to risk shifting behavior by investment fund managers. In the area of macroeforecasting, or market timing, Chapter 5 represents an extension to the scant Australian literature in this area. The results suggested that for the sample over the period examined, there is little evidence of successful market timing ability, a result that provides support for a widely held industry belief. Further, it was found that there was no clear dominance of one market timing model over the other, although interestingly, it was found that a cubic market model specification does fit the data quite well for nearly one third of the sample.

The contribution of Chapters 6 and 7 is to extend the empirical literature on fund manager behavior by investigating evidence of tournament effects in a dataset from one of the most sophisticated funds management market outside the United States. Chapter 6 employed a non-parametric contingency table-based methodology and extended the tournament literature through the use of three different representations of the annual tournament period and the examination of fund manager behavior against two ranking benchmarks, one endogenous and one exogenous. While the study in Chapter 6 is concerned primarily with evidence of risk-taking behavior on the part of fund managers, it can also be viewed as providing, albeit indirectly, empirical evidence on the question of whether benchmark choice may affect such behavior.

Chapter 7 continued the investigation of tournament behaviour by applying a parametric regression-based methodology to the dataset used in Chapter 6, updated to 2004. The tournament literature was further extended through investigation of a number of hypotheses dealing with the stability of the tournament effect, the presence of non-linearities in the relationship, and the impacts of fund age and fund size on tournament behaviour. The results, discussed in Chapter 7, indicate that while there is evidence of risk shifting behaviour, it is neither stable, nor as simple in form as earlier research suggested.

8.4. Limitations

The principle limitation of the demand side studies in this thesis is the dataset. While the data represents a large sample of investors seeking investment advice, it may not be representative of the population at large, and caution therefore needs to be exercised in drawing conclusions or inferences in relation to the broader population.

In relation to the supply side studies, the use of returns-based analysis to examine the performance and behavior of fund managers must be considered a less powerful technique than holdings-based analysis. However, the lack of access to data on fund holdings prevents use of this technique.

8.5. Directions for Future Research

The scope and structure of the thesis, as presented in Section 1.6, has been successfully achieved in the preceeding chapters. As with any major research undertaken, a number of decisions had to be taken concerning appropriate research design and methods of analysis. Given the breadth of the concept of investment risk, it was always apparent that the research in this thesis would raise a number of issues that would be beyond the scope of this thesis and would be the material for future research.

For example, following the demand side analysis in Chapters 2 to 4, further research into financial risk tolerance, using a sample more representative of the general population, may confirm the universality of these results. Additionally, further research could explore the ability of these demographics to predict investors risk tolerance score, or classify investors into broad risk tolerance groupings, out-of-sample.

From the supply-side analysis, the finding in Chapter 5 that a cubic market model specification fits the data quite well for nearly one third of the sample suggests a possible area worthy of further research effort, namely, an examination of performance in the context of higher moment models.

Finally, the analysis of tournament behaviour in Chapters 7 and 8 suggests that a more detailed analysis of the flow-performance relationship and its interaction with fund manager compensation could lead to a better understanding of the role of risk shifting and the nature of competition between fund managers.

References

.

Acker, D., & Duck, N. W. (2001). A Tournament Model of Fund Management. *Working Paper 01/529 University of Bristol*.

Ackert, L. F., Church, B. K., & Englis, B. (2002). The Asset Allocation Decision and Investor Heterogeneity: A Puzzle? *Journal of Economic Behavior and Organisation`47,* **47**, 423-433.

Admati, A. R., Bhattacharya, S., Pfleiderer, P., & Ross, S. A. (1986). On Timing and Selectivity. *Journal of Finance,* **41**(3), 715 - 732.

Aguilar, L. (2001). Women, Business and Finances: A Look to the Future. *Los Angeles Business Journal,* **8**(October), 4.

Atkinson, S. M., Baird, S. B., & Frye, M. B. (2003). Do Female Mutual Fund Managers Manage Differently? *Journal of Financial Research,* **26**(1), 1-18.

Bajtelsmit, V. L., & Bernasek, A. (1996). Why Do Women Invest Differently to Men. *Financial Counselling and Planning,* **7**, 1-9.

Bajtelsmit, V. L., Bernasek, A., & Jianakoplos, N. A. (1999). Gender Differences in Defined Contribution Pension Decisions. *Financial Services Review,* **8**, 1-10.

Bajtelsmit, V. L., & VanDerhei, J. L. (1997). Risk Aversion and Pension Investment Choices. In O. S. Mitchell (Ed.), *Positioning Pensions for the Year 2000* (pp. 45-66). Philadelphia: University of Pennsylvania Press.

Baker, H. K., & Haslem, J. A. (1974). The Impact of Investor Socioeconomic Characteristics on Risk and Return Preferences. *Journal of Business Research,* **2**, 469-476.

Barber, B. M., & Odean, T. (2001). Boys Will Be Boys: Overconfidence and Common Stock

Investment. *Quarterly Journal of Economics,* **116**(1), 261-292.

Barclay, M. J., Pearson, N. D., & Weisbach, M. S. (1998). Open-end Mutual Funds and Capital Gains Taxes. *Journal of Financial Economics,* **19**, 3-43.

Barsky, R. B., Juster, F. T., Kimball, M. S., & Shapiro, M. D. (1997). Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Study. *Quarterly Journal of Economics,* **112**, 537-579.

Basak, S., Pavlova, A., & Shapiro, A. (2002). Offsetting the Incentives: Risk Shifting and Benefits of Benchmarking in Money Management. *Working Paper, NYU Stern School of Business*.

Bello, Z. Y., & Janjigian, V. (1997). A Reexamination of the Market - Timing and Security - Selection Performance of Mutual Funds. *Financial Analysts Journal,* **Sept - Oct**(1997), 24 - 30.

Berkowitz, M. K., & Kotowitz, Y. (2000). Investor Risk Evaluation in the Determination of Management Incentives in the Mutual Fund Industry. *Journal of Financial Markets,* **3**, 365 - 387.

Bernasek, A., & Shwiff, S. (2001). Gender, Risk and Retirement. *Journal of Economic Issues,* **35**, 345-356.

Bernheim, B. D., Skinner, J., & Weinberg, S. (2001). What Accounts for the Variation in Retirement Wealth Among U.S. Households. *American Economic Review,* **91**(4), 832-
.

Bliss, R. T., & Potter, M. E. (2002). Mutual Fund Managers: Does Gender Matter? *Journal of Business & Economic Studies,* **8**(1), 1-15.

Blume, M. (1978). *The Changing Role of the Individual Investor*: John Wiley and Sons, New York.

Bowman, E. H. (1982). Risk Seeking by Troubled Firms. *Sloan Management Review,* **23**, 33-42.

Brown, K. C., Harlow, W. V., & Starks, L. T. (1996). Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual Fund Industry. *Journal of Finance,* **15**(1), 85 - 110.

Brown, R., Durbin, J., & Evans, J. (1975). Techniques for Testing the Constancy of Regression Relationships over Time. *Journal of the Royal Statistical Society,* **37**, 145 - 164.

Brown, S. J., W Goetzman, Ibbotson, R. G., & Ross, S. A. (1992). Survivorship Bias in Performance Studies. *Review of Financial Studies,* **5**, 553-580.

Bull, C., Schotter, A., & Weigelt, K. (1987). Tournaments and Piece Rates: An Experimental Study. *Journal of Political Economy,* **95**(1), 1-33.

Busse, J. A. (2001). Another Look at Mutual Fund Tournaments. *Journal of Financial and Quantitative Analysis,* **36**(1), 53-73.

Callan, V. J., & Johnson, M. (2002). Some Guidelines for Financial Planners in Measuring and Advising Clients About Their Levels of Risk Tolerance. *Journal of Personal Finance,* **1**, 31-44.

Capon, N., Fitzsimons, G. J., & Prince, R. A. (1996). An Individual Level Analysis of the Mutual Fund Investment Decision. *Journal of Financial Services Research,* **10**, 59-82.

Carhart, M., Carpenter, J. N., Lynch, A. W., & Musto, D. (2002). Mutual Fund Survivorship,. *Review of Financial Studies,* **15**, 1439-1463.

Carpenter, J. N., & Lynch, A. W. (1999). Survivorship Bias and Attrition Effects in Measures of Performance Persistence. *Journal of Financial Economics,* **54**, 337-374.

Chang, E. C., & Lewellen, W. G. (1984). Market Timing and Mutual Fund Investment Performance. *Journal of Business,* **57**(1), 57 - 72.

Chen, C., & Stockum, S. (1986). Selectivity, Market Timing and Random Behaviour of Mutual Funds: A Generalised Model. *Journal of Financial Research*, 87 - 96.

Chen, H., & Volpe, R. P. (2002). Gender Difference in Personal Financial Literacy Among

College Students. *Financial Services Review,* **11**, 289-307.

Chen, H.-L., & Pennacchi, G. (2001). Does Prior Performance Affect a Mutual Fund's Choice of Risk? Theory and Further Empirical Evidence. *Working Paper, University of Illinois at Urbana-Champaign.*

Chevalier, J., & Ellison, G. (1997). Risk Taking by Mutual Fund as a Response to Incentives. *Journal of Political Economy,* **105**(6), 1167-1200.

Chordia, T. (1996). The Structure of Mutual Fund Charges. *Journal of Financial Economics,* **41**, 3-39.

Christensen, R. (1990). *Log-Linear Models*. New York: Springer-Verlag.

Chunhachinda, P., Dandapani, K., Hamid, S., & Prakash, A. (1994). Efficacy of Portfolio Performance Measures: An Evaluation. *Quaterly Journal of Business and Economics,* **33**, 74 - 87.

Claire, A. D., Priestly, R., & Thomas, S. H. (1998). Reports of Beta's Death are Premature. *Journal of Banking and Finance,* **22**(9), 1207 - 1228.

Clark-Murphy, M., & Gerrans, P. (2001). Consultation and Resource Usage in Retirement Savings Decisions: Australian Evidence of Systematic Gender differences. *Financial Services Review,* **10**, 273-290.

Coggin, T., Fabozzi, F., & Rahman, S. (1993). The Investment Performance of US Equity Pension Fund Managers: An Empirical Investigation. *Journal of Finance,* **48**, 1039 - 1055.

Coggin, T., & Hunter, J. E. (1993). A Meta-Analysis of Mutual Fund Performance. *Review of Quantitative Finance and Accounting,* **3**(2), 189-201.

Cohn, R. A., Lewellen, W. G., Lease, R. C., & Schlarbaum, G. G. (1975). Individual Investor Risk Aversion and Investment Portfolio Composition. *Journal of Finance,* **30**(2), 605-620.

Connor, G., & Korajcyzk, R. (1991). The Attributes, Behavior and Performance of US Mutual

Funds. *Review of Quantitative Finance and Accounting,* **1**(1), 5-26.

Cooper, I., & Kaplanis, E. (1994). Home Bias in Equity Portfolios, Inflation Hedging and International Capital Market Equilibrium. *Review of Financial Studies,* **7**, 45-60.

Cumby, R. E., & Glen, J. D. (1990). Evaluating the Performance of International Mutual Funds. *Journal of Finance,* **45**(2), 497-521.

Davey, G. (2000). *Risk Tolerance, Risk Profiling and the Financial Planning Process*, from www.proquest.com.au

DelGuercio, D., & Tkac, P. (2002). The Determinants of the Flow of Funds of Managed Portfolios: Mutual Funds vs. Pension Funds. *Journal of Financial and Quantitative Analysis,* **4**, 523-557.

Droms, W. G. (1987). Investment Asset Allocation for PFP Clients. *Journal of Accountancy,* **163**(4), 114-118.

Dwyer, P. D., Gilkeson, J. H., & List, J. A. (2002). Gender Differences in Revealed Risk Taking: Evidence from Mutual Fund Investors. *Economics Letters,* **76**(2), 151-158.

Eagly, A. (1995). The Science and Politics of Comparing Women and Men. *American Psychologist,* **50**(3), 145-158.

Ehrenberg, R. G., & Bognanno, M. L. (1990a). Do Tournaments Have Incentive Effects? *Journal of Political Economy,* **98**(6), 1307- 1324.

Ehrenberg, R. G., & Bognanno, M. L. (1990b). The Incentive Effects of Tournaments Revisited: Evidence from the European PGA Tour. *Industrial and Labour Relations Review,* **43**(Special Issue), 74 - 88.

Estes, R., & Hosseini, J. (1988). The Gender Gap on Wall Street: An Empirical Analysis of Confidence in Investment Decision Making. *Journal of Psychology,* **122**(6), 577-590.

Fang, H., & Lai, T. Y. (1997). Co-Kurtosis and Capital Asset Pricing. *Financial Review,* **32**(2), 293 - 307.

Ferson, W. E., & Schadt, R. W. (1996). Measuring Fund Strategy and Performance in

Changing Economic Conditions. *Journal of Finance,* **51**(2), 425 - 461.

Fienberg., S. E. (1980). *The Analysis of Cross-Classified Categorical Data,* (Second ed.). Cambridge, Mass: MIT Press.

Fletcher, J. (1995). An Examination of the Selectivity and Market Timing Performance of UK Unit Trusts. *Journal of Business Finance and Accounting,* **22**(1), 143 - 156.

Friedman, B. (1974). Risk Aversion and the Consumer Choice of Health Insurance option. *Review of Economics and Statistics,* **56**, 209-214.

Garcia, O. M., & Begona, T. O. (2000). *Managers' Incentives to Mutual Fund Performance: An Empirical Investigation in the Spanish Market.*Unpublished manuscript, University of Cantabria. Spain.

Goetzman, W. N., & Ibbotson, R. G. (1994). Do Winners Repeat? *Journal of Portfolio Management,,* **3**, 9-18.

Goetzman, W. N., & Peles, N. (1997). Cognitive Dissonance and Mutual Fund Investors. *Journal of Financial Research,* **20**, 145-158.

Gollier, C., & Zeckhauser, R. J. (2002). Horizon Length and Portfolio Risk. *Journal of Risk and Uncertainty,* **24**, 195-212.

Goriaev, A., Palomino, F., & Prat, A. (2001). Mutual Fund Tournament: Risk Taking Incentives Induced by Ranking Objectives. *CEPR Discussion Paper No. 2794, Tilburg University.*

Goriaev, A. P., Nijman, T. E., & Werker, B. J. M. (2005). Yet Another Look at Mutual Fund Tournaments. *Journal of Empirical Finance,* **12**, 127-137.

Grable, J. E. (2000). Financial Risk Tolerance and Additional Factors That Affect Risk Taking in Everyday Money Matters. *Journal of Business and Psychology,* **14**(4), 625-630.

Grable, J. E., & Joo, S. (1997). Determinants of Risk Preference: Implication for the Family and Consumer Science Professionals. *Family Economics and Resource Management*

Biennial, **2**, 19-24.

Grable, J. E., & Joo, S. (1999). Factors Related to Risk Tolerance: A Further Examination. *Consumer Interests Annual,* **45**, 53-58.

Grable, J. E., & Joo, S.-H. (2000). A Cross-Disciplinary Examination of Financial Risk Tolerance. *Consumer Interests Annual,* **46**.

Grable, J. E., & Lytton, R. H. (1998). Investor Risk Tolerance: Testing the Efficacy of Demographics as Differentiating and Classifying Factors. *Financial Counseling and Planning,* **9**(1), 61-73.

Grable, J. E., & Lytton, R. H. (1999). Assessing Financial Risk Tolerance: Do Demographic, Socioeconomic and Attitudinal Factors Work? *Family Relations and Human Development/Family Economics and Resource Management Biennial,*, 80-88.

Green, J. R., & Stokey, N. L. (1983). A Comparison of Tournaments and Contracts. *Journal of Political Economy,* **91**(3), 349 - 364.

Grinblatt, M., & Titman, S. (1989). Adverse Risk Incentives and the Design of Performance - Based Contracts. *Management Science,* **35**(7), 807 - 822.

Grinblatt, M., & Titman, S. (1994). The Persistence of Mutual Fund Performance. *Journal of Finance,* **47**(5), 1997 - 1984.

Halek, M., & Eisenhauer, J. G. (2001). Demography of Risk Aversion. *Journal of Risk and Insurance,* **68**(1), 1-24.

Haliassos, M., & Bertaut, C., C. (1995). Why Do So Few Hold Stocks? *Economic Journal,* **105**, 1110-1129.

Hallahan, T. A., & Faff, R. W. (1999). An Examination of Australian Equity Trusts for Selectivity and Market Timing Performance. *Journal of Multinational Financial Management,* **9**, 387-402.

Hallahan, T. A., Faff, R. W., & McKenzie, M. (2003). An Exploratory Investigation of the Relation Between Risk Tolerance Scores and Demographic Characteristics. *Journal of*

Multinational Financial Management, **13**, 483-502.

Hallahan, T. A., Faff, R. W., & McKenzie, M. (2004). An Empirical Investigation of Personal Financial Risk Tolerance. *Financial Services Review,* **13**, 57-78.

Hanna, S., Gutter, M., & Fan, J. (1998). A Theory Based Measure of Risk Tolerance. *Proceedings of the Academy of Financial Services*, 10-27.

Hariharan, G., Chapman, K. S., & Domian, D. L. (2000). Risk Tolerance and Asset Allocation for Investors Nearing Retirement. *Financial Services Review,* **9**, 159-170.

Harlow, W. V., & Brown, K. C. (1990). Understanding and Assessing Financial Risk Tolerance: A Biological Perspective. *Financial Analysts Journal,* **46**(6), 50-62.

Hawley, C. B., & Fujii, E. T. (1993). An Empirical Analysis of Preferences for Financial Risk: Further Evidence on the Friedman-Savage model. *Journal of Post-Keynesian Economics,* **16**(2), 197-204.

Henrikson, R. (1984). Market Timing and Mutual Fund Performance: An Empirical Investigation. *Journal of Business,* **57**(1), 73 - 96.

Henrikson, R., & Merton, R. (1981). On Market Timing and Investment Performance: Statistical Procedures for Evaluating Forcasting Skills. *Journal of Business,* **54**(4), 513- 533.

Hey, J. D. (1999). Estimating Risk Preference Functions Using Experimental Methods. In L. Luini (Ed.), *Uncertain Decisions: Bridging Theory and Experiments* (pp. 109-128). Boston: Kluwer Academic.

Hinz, R. P., McCarthy, D. D., & Turner, J. A. (1997). Are Women Conservative Investors. In I. S. Mitchell (Ed.), *Positioning Pensions for the Year 2000* (pp. 91-103). Philadelphia: University of Pennsylvania Press.

Holmstrom, B. (1982). Moral Hazard in Teams. *Bell Journal of Economics,* **13**(2), 323-340.

Hudgens, G. A., & Fatkin, L. T. (1985). Sex Differences in Risk-Taking: Repeated Sessions on a Computer-Simulated Task. *Journal of Psychology,* **119**(3), 197-206.

Ippolito, R. A. (1992). Consumer Reaction to Measures of Poor Quality Funds from the Mutual Fund Industry. *Journal of Law and Economics,* **35**(1), 45 - 70.

Ippolito, R. A. (1993). On Studies of Mutual Fund Performance, 1962 - 1991. *Financial Analysts Journal,* **49**(January-February), 42 - 50.

Jackson, D. N., Hourany, L., & Vidmar, N. J. (1972). A Four Dimensional Interpretation of Risk Taking. *Journal of Personality,* **40**(3), 483-501.

Jacobs, B. I., & Levy, K. N. (1996). Residual Risk: How Much is too Much? *Journal of Portfolio Management,,* **22**(3), 10-16.

Jagannathan, R., & Korajczyk, R. (1986). Assessing the Market Timing Performance of Managed Portfolios. *Journal of Business,* **59**(2), 217 - 235.

Jensen, M. C. (1968). The Performance of Mutual Funds in the Period 1945 - 1964. *Journal of Finance,* **23**(2), 389 - 415.

Jianakoplos, N. A., & Bernasek, A. (1998). Are Women More Risk Averse? *Economic Enquiry,* **36**(4), 620-630.

Johnson, J. E. V., & Powell, P. L. (1994). Decision Making, Risk and Gender: Are Managers Different? *British Journal of Management,* **5**(2), 123-138.

Kahn, R. N., & Rudd, A. (1995). Does Historical Performance Predict Future Performance? *Financial Analysts Journal,* **51**(6), 43-52.

Kempf, A., & Ruenzi, S. (2003). Tournaments in Mutual Fund Families. *EFA 2003 Annual Conference Paper, University of Cologne Finance Discussion Paper No 2002-1*.

Khorana, A., Servaes, H., & Tufano, P. (2005). Explaining the Size of the Mutual Fund Industry Around the World. *Journal of Financial Economics,* **78**(1), 145-185.

Kinsella, K., & Gist, Y. J. (1998). *International Brief - Mortality and Health*: Series IB/92-2 Gender and Aging, U.S.Census Bureau, Washington, DC.

Knoeber, C. R., & Thurman, W. N. (1994). Testing the Theory of Tournaments: An Empirical Analysis of Broiler Production. *Journal of Labor Economics,* **12**(2), 155-179.

Kon, S. J. (1983). The Market Timing Performance of Mutual Fund Managers. *Journal of Business,* **56**(3), 321 - 347.

Koski, J. L., & Pontiff, J. (1999). How are Derivatives Used? Evidence from the Mutual Fund Industry. *Journal of Finance,* **54**(2), 791-810.

Kothari, S. P., & Warner, J. B. (2001). Evaluating Mutual Fund Performance. *Journal of Finance,* **56**(5), 1985-2010.

Kover, A. (1999). Okay, Women Could Use Special Advice About Investing but Why Does it Have to Be So Brainless? *Fortune, 139,* 129-132.

Lakonishok, J. A., Shleifer, A., & Vishny, R. W. (1992). The Structure and Performance of the Money Management Industry. *Brookings Papers on Economic Activity, Microeconomic*, 339 - 391.

Lazear, E. P., & Rosen, S. (1981). Rank-Order Tournaments as Optimum Labor Contracts. *Journal of Political Economy,* **89**, 841-864.

Leamer, E. E. (1983). Let's Take the Con Out of Econometrics. *American Economic Review,* **73**(1), 31-43.

Lee, C.-F., & Rahman, S. (1990). Market Timing, Selectivity and Mutual Fund Performance: An Empirical Examination. *Journal of Business,* **63**(2), 261 - 278.

Lehmann, B. N., & Modest, D. M. (1987). Mutual Fund Performance Evaluation: A Comparison of Benchmarks and Benchmark Comparisons. *Journal of Finance,* **42**(2), 233 - 265.

Leigh, J. P. (1986). Accounting for Tastes: Correlates of Risk and Time Preferences. *Journal of Post Keynesian Economics,* **9**(1), 17-31.

Lewellen, W. G., Stanley, K. L., Lease, R. C., & Schlarbaum, G. G. (1978). Some Direct Evidence on the Dividend Clientele Phenomenon. *Journal of Finance,* **33**(5), 1385-1399.

Lo, A., & Mackinlay, A. C. (1990). Data Snooping Biases in Tests of Financial Asset Pricing

Models. *Review of Financial Studies,* **3**, 431 - 467.

Markowitz, H. (1952). Portfolio Selection. *Journal of Finance,* **7**(1), 77-91.

Markowitz, H. (1959). *Portfolio Selection: Efficient Diversification of Investments* (Second ed.). Cambridge, Massachusetts: Basil Blackwell.

Masters, R. (1989). Study Examines Investors' Risk-taking Propensities. *Journal of Financial Planning*(July), 151-155.

Masters, R., & Meier, R. (1988). Sex Differences and Risk-taking Propensity of Entrepreneurs. *Journal of Small Business Management*, 31-35.

McInish, T. H. (1982). Individual Investors and Risk-taking. *Journal of Economic Psychology,* **2**(2), 125-136.

Mookherjee, D. (1984). Optimal Incentive Schemes with Many Agents. *Review of Economic Studies,* **51**(3), 433-446.

Morin, R. A., & Suarez, A. F. (1983). Risk Aversion Revisited. *Journal of Finance,* **38**(4), 1201-1216.

Nalebuff, B. J., & Stiglitz, J. E. (1983). Information, Competition, and Markets. *AEA Papers and Proceedings,* **73**(2), 278 - 283.

Olsen, R. A., & Cox, C. M. (2001). The Influence of Gender on the Perception and Response to Investment Risk: The Case of Professional Investors. *Journal of Psychology and Financial Markets,* **2**(1), 29-36.

Oyer, P. (1998). Fiscal Year Ends and Nonlinear Incentive Contracts: The Effect on Business Seasonality. *Quarterly Journal of Economics,* **113**(1), 149-185.

Palomino, F., & Prat, A. (2003). Risk Taking and Optimal Contracts for Money Managers. *RAND Journal of Economics,* **34**(1), 113 - 137.

Palsson, A.-M. (1996). Does the Degree of Relative Risk Aversion Vary With Household Characteristics? *Journal of Economic Psychology,* **17**(6), 771-787.

Phelps, S., & Detzel, L. (1997). The Nonpersistence of Mutual Fund Performance. *Quarterly*

Journal of Business and Economics, **36**(2), 55-69.

Powell, G. (1990). One More Time: Do Male and Female Managers Differ? *Academy of Management Executive,* **4**(3), 68-75.

Powell, M., & Ansic, D. (1997). Gender Difference in Risk Behaviour in Financial Decision-making: An Experimental Analysis. *Journal of Economic Psychology,* **18**(6), 605-628.

Prakash, A. J., & Bear, R. M. (1986). A Simplifying Performance Measure Recognizing Skewness. *Financial Review,* **21**(1), 135 - 144.

Prince, M. (1992). Women, Men and Money Styles. *Journal of Economic Psychology,* **14**(1), 175-182.

Quandt, R. E. (1958). The Estimation of the Parameters of a Linear Regression System Obeying Two Seperate Regimes. *Journal of the American Statistical Association,* **53**, 873 - 880.

Quandt, R. E. (1960). Tests of Hypothesis that a Linear Regression System Obeys Two Seperate Regimes. *Journal of the American Statistical Association,* **55**, 324 - 330.

Qui, J. (2003). Termination Risk, Multiple Managers and Mutual Fund Tournaments. *European Finance Review,* **7**(2), 161-190.

Riley, W. B., & Chow, K. V. (1992). Asset Allocation and Individual Risk Aversion. *Financial Analysts Journal,* **48**(6), 32-37.

Roszkowski, M. J., Snelbecker, G. E., & Leimberg, S. R. (1993). Risk Tolerance and Risk Aversion. In S. R. Leimberg, M. J. Satinsky & R. T. Leclair (Eds.), *The tools and techniques of financial planning*. Cincinnati, OH.: National Underwriter.

Schirripa, F., & Tecotzky, N. D. (2000). An Optimal Frontier. *Journal of Portfolio Management,,* **26**(4), 29-40.

Schooley, D. K., & Wordon, D. D. (1996). Risk Aversion Measures: Comparing Attitudes and Asset Allocation. *Financial Services Review,* **5**(2), 87-99.

Schubert, R., Brown, M., Gysler, M., & Brachinger, H. W. (1999). Financial Decions-

Making: Are Women Really More Risk-Averse. *AEA Papers and Proceedings,* **89**(2), 381-385.

Scott, R., & Horvath, P. (1980). On the Direction of Preference for Moments of Higher Order than Variance. *Journal of Finance,* **35**(4), 915 - 919.

Secord, P. F., & Backman, C. W. (1964). *Social Psychology*. New York: McGraw-Hill.

Shaw, K. L. (1996). An Empirical Analysis of Risk Aversion and Income Growth. *Journal of Labor Economics,* **14**(4), 626-653.

Shukla, R., & Trzcinka, C. (1994). Persistent Performance in the Mutual Fund Market: Tests with Funds and Investment Advisers. *Review of Quantative Finance and Accounting,* **4**(2), 115 - 135.

Siegrist, M., Cvetkovich, G., & Gutscher, H. (2002). Risk Preference Predictions and Gender Stereotypes. *Organizational Behavior and Human Decision Processes,* **87**(1), 91-102.

Simons, K. (1999). Should US Investors Invest Overseas? *Federal Reserve Bank of Boston New England Economic Review*(Nov), 29-40.

Sinclair, N. A. (1990). Market Timing Ability of Pooled Superannuation Funds January 1981 to December 1987. *Accounting and Finance,* **30**(1), 51 - 65.

Sirri, E. R., & ., P. T. (1992). The Demand for Mutual Fund Services by Individual Investors. *Working Paper, Harvard University*.

Sirri, E. R., & Tufano, P. (1998). Costly Search and Mutual Fund Flows. *Journal of Finance,* **54**(5), 1589-1623.

Slovic, P. (1966). Risk-taking in Children: Age and Sex Differences. *Child Development,* **37**, 169-176.

Stephens, A., & Proffitt, D. (1991). Performance Measurement when Return Distributions are Nonsymmetric. *Quaterly Journal of Business and Economics,* **30**(4), 23 - 41.

Stinerock, R., Stern, B. B., & Solomon, M. R. (1991). Sex and Money: Gender Differences in the Use of Surrogate Consumers for Financial Decision Making. *Journal of*

Professional Services Marketing, **7**(2), 167-182.

Sunden, A. E., & Surette, B. J. (1998). Gender Differences in the Allocation of Assets in Retirement Savings Plans. *AEA Papers and Proceedings*, 207-211.

Sung, J., & Hanna, S. (1996). Factors Related to Risk Tolerance. *Financial Counsel and Planning,* **7**, 11-20.

Taylor, J. (2003). Risk-taking Behavior in Mutual Fund Tournaments. *Journal of Economic Behavior and Organisation,* **50**(3), 373-383.

Tong, K.-K., & Leung, K. (2002). Tournament as a Motivational Strategy: Extension to Dynamic Situations With Uncertain Duration. *Journal of Economic Psychology,* **23**(3), 399 - 420.

Treynor, J., & Mazuy, M. (1966). Can Mutual Funds Outguess the Market. *Harvard Business Review,* **44**, 131 - 136.

Vandegrift, D., & Brown, P. (2003). Task Difficulty, Incentive Effects and the Selection of High-Variance Strategies: An Experimental Examination of Tournament Behavior. *Labour Economics,* **10**(4), 481-497.

Verheul, I., Risseeuw, P., & Bartelse, G. (2002). Gender Differences in Strategy and Human Resource Management: The Case of Dutch Real Estate Brokerage. *International Small Business Journal,* **20**(4), 443-476.

Wallach, M. A., & Kogan, N. (1961). Aspects of Judgment and Decision-Making: Interrelationships and Changes With Age. *Behavioral Science,* **6**, 23-26.

Wang, H., & Hanna, S. (1997). Does Risk Tolerance Decrease With Age? *Financial Counseling and Planning,* **8**(2), 27-32.

White, H. (1980). Heteroskedasticity- Consistent Covariance Matrix Estimators and a Direct Test for Heteroskedasticity. *Econometrica,* **48**, 817 - 838.

Wilcox, R. T. (2003). Bargain Hunting or Star Gazing? Investors Preferences for Stock Mutual Funds. *Journal of Business,* **76**(4), 645-663.

Xiao, J. J., Alhabeeb, M. J., Gong-Soong, H., & Haynes, G. W. (2000). Risk Tolerance of Family Business Owners. *Consumer Interests Annual,,* **46**, 1-7.